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How does government spending news affect interest rates? Evidence from the United States[☆]

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ABSTRACT

This study analyzes the effects of news shocks to U.S. government spending on interest rates, especially long-term interest rates, and investigates the role of agents' expectations in the propagation of government spending to interest rates. Using large Bayesian vector autoregressive models with sufficient information, we find that news about increases in government spending induce significant increases in both short- and long-term interest rates while the effects of government spending surprise shocks on interest rates are mixed and ambiguous. Government spending news shocks in the baseline model account for around 10% of the variance in forecast errors in long-term interest rates, which is much more important than government spending itself. Using empirical dynamic term structural models, we further decompose increases in long-term interest rates into changes in expectations of future monetary policy and changes in term premiums. We find that an increase in the long-term interest rate after a positive government spending news shock mainly reflects higher expected future short-term interest rates, which demonstrates the importance of the coordination between fiscal and monetary policy communication.

1. Introduction

Understanding how the dynamics of interest rates are affected by government expenditure has long been an important issue in the financial economics and macroeconomics literature. In theory, an exogenous increase in public expenditure should drive up interest rates with an exogenous shift in aggregate demand. However, despite decades of work on identifying exogenous changes in government spending, existing empirical evidence does not fully support the theoretical prediction. Evans and Marshall (2007) find no evidence of significant responses of interest rates to fiscal shocks. Mountford and Uhlig (2009) find a significant negative effect of a government expenditure shock on interest rates and a mildly positive one once the authors impose a time restriction that allows expenditure to increase only at one year after a hypothetical announcement. Fisher and Peters (2010) find that the rates of three-month Treasury bills fall as government spending rises.

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Among recent works, Ramey (2011), Leeper et al. (2013) and Forni and Gambetti (2016) illustrate that fiscal policy actions are largely anticipated because of the existence of legislative and implementation lags. Fiscal foresight generates misalignment between the time at which fiscal policy begins to show its effects and the time at which such policy is actually incurred. Ignoring this time difference may lead to a misspecification of the information set needed to properly evaluate the effects of the fiscal policy. For example, during the 2011 U.S. debt ceiling crisis, long-term interest rates decreased significantly from May 2011 with rising expectations of future spending cuts since the Republican Party firmly demanded that President Obama reduce the deficit in exchange for an increase in the debt ceiling. The crisis finally ended in August with the passage of the Budget Control Act of 2011, which included $900 billion in spending cuts over the next ten years. As another example, Donald Trump's White House victory quickly drove U.S. interest rates to high levels at the end of 2016 because of the incoming president's promised infrastructure spending and tax cuts, while the passage of the tax reform bill itself had a modest effect on the bond market in December 2017. Given the foregoing, this study focuses on the effect of news about government spending[1] on U.S. Treasury yields and investigates the role of agents' expectation in the propagation of government expenditure to interest rates.

We carry out our analysis in two steps. First, following Ellahie and Ricco (2017), we employ the large Bayesian vector autoregressive (BVAR) models developed by Bańbura et al. (2010) to solve the problem brought about by fiscal foresight, as shown by Leeper et al. (2013) and Forni and Gambetti (2016). Large BVAR models also allow us to include several financial variables related to financial market conditions, which might be important for the transmission of government spending news shocks to interest rates. In the benchmark analysis, we identify government spending news shocks using the maximum forecast error variance (MFEV) approach advocated by Barsky and Sims (2011) and Francis et al. (2014). We assume that news shocks to U.S. government spending can best explain future movements in government spending over a horizon of 20 quarters and are orthogonal to government spending surprise shocks, which are identified using sign restrictions as in Enders et al. (2011). Additional identification schemes such as that proposed by Forni and Gambetti (2016) are employed to check the robustness of the results. Our work is closely related to Ben Zeev and Pappa (2017), who compare defense spending news shocks identified using the MFEV approach with Ramey (2011) news shocks. Second, after analyzing the effect of news about government spending on short- and long-term interest rates, we investigate the channels through which government spending news shocks change interest rates, especially long-term interest rates, which is seldom examined by previous empirical studies. Using the empirical dynamic term structural models of Bauer et al. (2012), we decompose changes in long-term interest rates into changes in risk-neutral interest rates, which reflect the future path of the monetary policy, and changes in term premiums and consider the effect of government spending news through the channels related to these two components.

Our main findings are as follows. First, our estimated government spending news shocks contain valuable information on future changes in government spending, which capture several important budget-related legislative activities in the history of the United States[2] Second, we find that news about increases in government spending induces significant increases in both short- and long-term interest rates while the government spending surprise shocks identified by sign restrictions have no significant effect on interest rates, which is in line with previous studies such as Evans and Marshall (2007). The government spending news shocks in the baseline model account for 10% of the variance in the forecast errors in 10-year Treasury yields, which is much more important than government spending itself. Thus, they should not be neglected when evaluating fiscal policy. Third, we find that increases in 10-year U.S. Treasury yields after positive government spending news shocks are mainly caused by higher risk-neutral interest rates. The risk-neutral rate which reflects the future path of monetary policy, increases for around six quarters and then decreases while the term premium tends to decrease first and then increase after news about rises in government spending. This result indicates that the fiscal authority plays an important role in shaping expectations of future monetary policy.

The remainder of the paper is organized as follows. We describe the empirical approach in Section 2 and present our data in Section 3. The BVAR results and robustness checks are in Section 4. Section 5 concludes.

2. Empirical strategy

We first study the relationship between fiscal behaviors and Treasury yields in a vector autoregression (VAR) framework similar to that of Evans and Marshall (2007). Because of the existence of legislative and implementation lags, fiscal policy actions are largely anticipated, which renders the information set of econometricians strictly smaller than that of economic agents and causes the problem of "non-fundamentalness" or informational insufficiency, as shown by Leeper et al. (2013). To address this problem, we employ a large BVAR model to approximate the flow of information received by economic agents, which includes expectations of government spending, as well as many forward-looking variables such as financial market variables and information from surveys.

[1] Government spending news shocks can also be called "anticipated" shocks, which have delayed effects on spending but on impact, affect agents' expectations. However, government spending surprise shocks are "unanticipated" shocks, which affect spending on impact and are observed only when agents see the actual spending.

[2] Following Ben Zeev and Pappa (2017), we further compare MFEV news shocks with the news shocks based on Forni and Gambetti (2016) in Appendix B.1. Our shocks use a less restrictive identifying assumption and do not rely on Forni and Gambetti (2016) 'NEWS' variable which is constructed from forecasters' expectations of future fiscal expenditure.

Next, we decompose 10-year Treasury yields using an affine Gaussian dynamic term structure model (DTSM) to explore the channels through which fiscal shocks may affect interest rates. We consider two channels. First, an increase in government spending is expected to cause inflationary pressure in an economy producing or enlarging positive output gaps. Traders in the bond market may anticipate that inflation-targeting central banks will increase the interest rate to prevent inflation from increasing in the future, which makes long-term Treasury yields rise now. Second, a rise in government spending may create more debt in the future. If government budget deficits are large and persistent, investors may worry about the government's ability to pay off its debt or credit ratings of government bonds, and therefore require more compensation for Treasury bonds with long maturities.

In the following subsections, we describe in detail the DTSM, the large BVAR estimation, and shock identification strategy.

2.1. Decomposition of interest rates

Following the seminal work of Ang and Piazzesi (2003), we use the DTSM to decompose long-run bond yields into risk-neutral interest rates, which reflects expectations of future monetary policy and the long-maturity term premiums related to risk compensation. We model bond prices using a vector of m risk factors, X_t, which is assumed to follow a first-order Gaussian VAR under the objective probability measure $\mathbb{P}$:

$$X_{t+1} = \mu + \Phi X_t + D\,\nu_{t+1}, \quad \nu_t \sim \mathcal{N}(0,\, \mathrm{I}_m), \tag{1}$$

where D is a lower triangular matrix and I_m is an m-dimensional identity matrix. The short-term interest rate r_t is an affine function of the risk factors:

$$r_t = \delta_0 + \delta_1' X_t, \tag{2}$$

where δ_0 is a scalar and δ_1 is an m-dimensional vector. Finally, there exists a stochastic discount factor (SDF) that prices all assets under no arbitrage, which is affine as in Duffee (2002):

$$-\log(M_{t+1}) = r_t + \frac{1}{2}\,\lambda_t'\,\lambda_t + \lambda_t'\,\nu_{t+1}, \tag{3}$$

where the vectors of risk prices (λ) are affine in the same risk factors,

$$\lambda_t = \lambda_0 + \lambda_1 X_t, \tag{4}$$

for m-dimensional vector λ_0 and $m \times m$ matrix λ_1. As a consequence of the above assumptions, a risk-neutral probability measure $\mathbb{Q}$ exists such that the price of an n-period default-free zero coupon bond is $P_t^{(n)} = \mathbb{E}_t^{\mathbb{Q}}(\exp(-\prod_{j=0}^{n-1} r_{t+j}))$, and the risk factors under risk neutrality also follow a Gaussian VAR:

$$X_{t+1} = \mu^{\mathbb{Q}} + \Phi^{\mathbb{Q}} X_t + D\,\nu_{t+1}^{\mathbb{Q}}, \quad \nu_t^{\mathbb{Q}} \sim \mathcal{N}(0,\, \mathrm{I}_m). \tag{5}$$

The prices of risk determine how VAR parameters under the $\mathbb{P}$ measure and the $\mathbb{Q}$ measure are related:

$$\mu^{\mathbb{Q}} = \mu - D\,\lambda_0 \tag{6}$$

$$\Phi^{\mathbb{Q}} = \Phi - D\,\lambda_1. \tag{7}$$

Let $y_t^{(n)} = -\log(P_t^{(n)})/n$ denote the yields of the n-period zero-coupon bond. Ang and Piazzesi (2003) show that the assumptions above imply that zero-coupon yields are affine in X_t

$$y_t^{(n)} = -\frac{\mathcal{A}_n}{n} - \frac{\mathcal{B}_n'}{n} X_t, \tag{8}$$

where $\mathcal{A}_n = \mathcal{A}_n(\mu^{\mathbb{Q}},\, \Phi^{\mathbb{Q}},\, \delta_0,\, \delta_1,\, D)$ is a scalar and $\mathcal{B}_n = \mathcal{B}_n(\delta_1,\, \Phi^{\mathbb{Q}})$ is an $m \times 1$ vector that satisfy the recursions:

$$\mathcal{A}_{n+1} = -\delta_0 + \mathcal{A}_n + \mathcal{B}_n'\,\mu^{\mathbb{Q}} + \frac{1}{2}\,\mathcal{B}_n' D D'\,\mathcal{B}_n \tag{9}$$

$$\mathcal{B}_{n+1}' = -\delta_1' + \mathcal{B}_n'\,\Phi^{\mathbb{Q}}, \tag{10}$$

with initial values $\mathcal{A}_0 = 0$ and $\mathcal{B}_0 = 0$. On the other hand, the risk-neutral yields (the observed yields that would prevail if investors were risk-neutral) can be calculated using

$$\tilde{y}_t^{(n)} = -\frac{\tilde{\mathcal{A}}_n}{n} - \frac{\tilde{\mathcal{B}}_n'}{n} X_t, \tag{11}$$

where $\tilde{\mathcal{A}}_n = \mathcal{A}_n(\mu,\, \Phi,\, \delta_0,\, \delta_1,\, D)$ and $\tilde{\mathcal{B}}_n = \mathcal{B}_n(\delta_1,\, \Phi)$ follow the same iterations in Eqs. (9) and (10) with $\mu^{\mathbb{Q}}$ and $\Phi^{\mathbb{Q}}$ replaced by μ and Φ. These risk-neutral yields reflect policy expectations over the lifetime of the bond. Furthermore, the yield term premium $ytp_t^{(n)}$ is defined as the difference between the actual and risk-neutral rates

$$ytp_t^{(n)} = y_t^{(n)} - \tilde{y}_t^{(n)}. \tag{12}$$

Denote by $\boldsymbol{y}_t = (y_t^{(n_1)}, y_t^{(n_2)}, \ldots, y_t^{(n_k)})'$ the vector of observed yields on day t. We use Treasury yields with maturities from one to ten years in this study, i.e., $n_k = 10$. As in Bauer et al. (2012), we take the risk factors X_t to be the first three principal components of observed yields. That is, denoting W the $3 \times n_k$ matrix with rows corresponding to the first three eigenvectors of the covariance matrix of $\boldsymbol{y}_t$, we have $X_t = W\boldsymbol{y}_t$. To calculate the risk-neutral rates and term premiums, we estimate the DTSM using Bauer et al. (2012) method which adapts the two-step estimation approaches of Joslin et al. (2011) by replacing the ordinary least squares estimates of the VAR system in the first step by simulation-based bias-corrected estimates since the high persistence of interest rates likely generates serious small-sample bias in estimates of the VAR parameters.

2.2. Large BVAR model

Since we include many variables to approximate the information set of economic agents, we use the large BVAR model to overcome the "curse of dimensionality" problem, which uses informative priors to shrink the richly parameterized VAR toward a more parsimonious model. Following Giannone et al. (2015), the appropriate degree of shrinkage is selected by treating hyper-parameters as any other unknown parameter, setting a prior for them and using the data to evaluate their posterior.

Specifically, let Y_t denote a large vector of n variables. Similar to Evans and Marshall (2007), we partition Y_t into $\left[Z_t', F_t'\right]'$, where Z_t is an $n_z \times 1$ vector of the macroeconomic series that includes many forward-looking variables plus the effective federal funds rate and F_t is an $(n - n_z) \times 1$ vector of the Treasury yields or the decomposition of long-term yields. We estimate the following reduced-form VAR(p) model:

$$Y_t = c + \sum_{\ell=1}^{p} B_\ell Y_{t-\ell} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \Sigma), \tag{13}$$

where c is an $n \times 1$ vector of the constants, B_ℓ, $\ell = 1, \ldots, p$ are $n \times n$ autoregressive matrices, and ϵ_t is an $n \times 1$ vector of the reduced-form errors with variance-covariance matrix Σ. Defining $B_+ := \left[c, B_1, \ldots, B_p\right]'$ and $\beta := vec(B_+)$, where $vec(\cdot)$ is the vector operator, we set a normal inverse-Wishart prior for β and Σ, namely,

$$\beta|\Sigma \sim \mathcal{N}(b(\gamma), \Sigma \otimes \Omega(\gamma)) \tag{14}$$

$$\Sigma \sim \mathcal{IW}(\Psi; n+2), \tag{15}$$

where $b(\gamma)$ and $\Omega(\gamma)$ are typical functions of a low-dimensional vector of the hyper-parameters γ. Moreover, we assume that the matrix Ψ is diagonal with $n \times 1$ elements ψ along the main diagonal, and we fix the elements of ψ using sample information; in other words, we pin down their value using the variance in the residuals from a univariate autoregressive model of order p for each variable in Y_t. As for the conditional Gaussian prior for β, we combine the Minnesota prior, sum-of-coefficients prior and dummy-initial-observation prior. The Minnesota prior treats all the equations in the VAR as centering on the random walk process with drift. The sum-of-coefficients prior and dummy-initial-observation prior are incorporated into the VAR to circumvent the unit root and cointegration problems. As the posterior of the hyper-parameters does not admit a closed-form solution, we implement the Markov chain Monte Carlo algorithm to simulate the posterior of the coefficients of the BVAR, including the hyper-parameters. Further details on the prior selection and posterior simulation can be found in Giannone et al. (2015) and Ellahie and Ricco (2017).

2.3. Identification

Define $u_t \sim \mathcal{N}(0, \mathrm{I}_n)$ as the $n \times 1$ vector of mutually orthogonal structural shocks. Identifying structural shocks amounts to finding some linear mapping A with $\epsilon_t = A u_t$. From Eq. (13), the vector moving average representation of Y_t is $Y_t = \Theta(L)\epsilon_t$ where $\Theta(L) = \sum_{i=0}^{\infty} \Theta_i L^i$, and therefore, the corresponding structural vector moving average representation of Y_t is $Y_t = \Theta(L) A u_t = \Xi(L) u_t$, where $\Xi(L) = \Theta(L) A = \sum_{i=0}^{\infty} \Xi_i L^i$ and $\Xi_i = \Theta_i A$.

The key restriction that Eq. (13) imposes on A is $\Sigma = \mathbb{E}\left[A u_t u_t' A'\right] = AA'$. However, this restriction is not sufficient to pin down a unique A matrix because for any $n \times n$ matrix $\tilde{A}$ satisfying $\Sigma = \tilde{A}\tilde{A}'$ and $n \times n$ orthogonal matrix Q such that $QQ' = \mathrm{I}_n$, the alternative matrix $A = \tilde{A}Q$ also satisfies $\Sigma = AA'$. Thus, for some arbitrary matrix $\tilde{A}$ with $\Sigma = \tilde{A}\tilde{A}'$ (e.g., the lower triangular Cholesky decomposition of Σ), the identification reduces to choosing an orthogonal matrix Q such that the structural moving average matrix $\Xi_i = \Theta_i \tilde{A} Q$ satisfies some ad hoc identification assumptions.

In this study, we identify two shocks: the government spending surprise shock u_t^s and the government spending news shock u_t^n. Without loss of generality, we order the surprise shock first. To find the two orthogonal vectors $[q_s, q_n]$ in Q related to the government spending surprise and news shocks, we first use the sign-restriction approach to obtain q_s and then the MFEV method to achieve q_n. A detailed discussion is provided below.

2.3.1. The government spending surprise shock

We identify the government spending surprise shock using the sign-restriction method employed by Mountford and Uhlig (2009) and Enders et al. (2011). Table 1 summarizes the sign-restriction on the structural impulse response with

Table 1
Sign restrictions. *Note*: Responses of variables such as government spending (G), output (GDP), government surplus (SUR), private investment (INV), inflation (π), and federal funds rate (R) are restricted to be positive (+) or negative (−) up to k periods.

Shocks	Variables					
	G	GDP	SUR	INV	π	R
Government spending surprise shock	+	+	-	-	+	
Monetary policy shock		+		+	+	-
Business cycle shock		+		+	-	

respect to q_s. Following Enders et al. (2011), we define and identify the unanticipated government spending shock as the one that jointly stimulates government spending (G), output (GDP), and inflation (π), while suppressing government surplus (SUR) and private investment (INV) up to k periods following its impact. Our principle for choosing the sign restriction is to keep the set of restricted variables as small as possible while preserving the orthogonality conditions to ensure that the unanticipated government spending shock is orthogonal to the business cycle shock and monetary policy shock. To see this, we also demonstrate the sign restrictions on the monetary policy shock (where R stands for the federal funds rate) and the business cycle shock in Table 1 similar to Enders et al. (2011). The different responses of output, investment, and inflation can help us sort the government spending shock from the two other shocks.

2.3.2. Government spending news shock

To identify the anticipated government spending shock, we applied the MFEV approach as in Barsky and Sims (2011) and Francis et al. (2014).[3] To see the intuition of this approach, assume that the log of government spending g_t evolves according to the following process:

$$g_t = \nu(L)\, u_t^s + \mu(L)\, u_t^n + \delta(L)\, \xi_t. \tag{16}$$

where u_t^s is the surprise shock, u_t^n is the news shock, and ξ_t is a vector of the other structural shocks that possibly affect government spending such as the business cycle shock. The lag polynomials are expressed as $\nu(L) = \sum_{i=0}^{\infty} \nu_i L^i$, $\mu(L) = \sum_{i=0}^{\infty} \mu_i L^i$, and $\delta(L) = \sum_{i=0}^{\infty} \delta_i L^i$ with restrictions such that $\nu_0 \neq 0$ and $\mu_i = 0,\ \forall i < s,\ s \geq 1$, which means that u_t^n is materialized in t but affects government spending with at least a lag. In the benchmark model, we assume that structural shocks except the government spending surprise and news shocks play minor roles in explaining fluctuations in the government spending process.[4] Therefore, after the government spending surprise shock u_t^s is identified and controlled for, the news shock u_t^n is identified as the shock that best explains all the remaining variations in government spending over a horizon of several periods and that is orthogonal to the surprise shock. It is obvious that the identification of government spending news shocks relies heavily on whether government spending surprise shocks are well identified. Thus, different from previous studies such as Barsky and Sims (2011) that identify surprise shocks only using the Cholesky decomposition, we combine different identification schemes with the MFEV method, using sign restrictions to identify surprise shocks in the benchmark model and recursive identification in the robustness checks.

To implement the MFEV approach, we place the government spending variable first in the VAR system, and the share of the forecast error variance in government spending attributable to shock $j = s,\ n$ at horizon h, is given as

$$\Delta_i(h) = \frac{e_1' \left(\sum_{\tau=0}^{h} \Theta_\tau \tilde{A} q_j q_j' \tilde{A}' \Theta_\tau' \right) e_1}{e_1' \left(\sum_{\tau=0}^{h} \Theta_\tau \Sigma \Theta_\tau' \right) e_1}, \tag{17}$$

where e_1 is the $n \times 1$ selection vector with one in the first element and zero otherwise. We identify the anticipated government spending shock q_n as the solution to the following optimization problem

$$q_n = \arg\max \sum_{h=0}^{H} \Delta_n(h) \tag{18}$$

s.t

$$q_n(1) = 0 \tag{19}$$

$$q_s' q_n = 0 \tag{20}$$

$$q_n' q_n = 1. \tag{21}$$

[3] Subsequent studies that have adopted this method include Kurmann and Otrok (2013) and Nam and Wang (2015) to identify total factor productivity (TFP) news shocks, Zeev and Khan (2015) to identify investment-specific news shocks, and Ben Zeev and Pappa (2017) to identify defense spending news shocks.

[4] We relax this assumption in the robustness checks.

The restriction in Eq. (19) requires that the identified news shock has no contemporaneous effect on government spending. The second restriction ensures that the government spending news shock is orthogonal to the surprise shock. The third constraint restricts q_n to have a unit length.

3. Description of the data

The benchmark analysis is carried out on a panel of 27 quarterly series from 1974:Q3 to 2018:Q4 describing the U.S. economy[5] Most of the data are from the National Income and Product Accounts available from the Bureau of Economic Analysis and the Federal Reserve Economic Data (FRED) available from the Federal Reserve Bank of St. Louis. We categorize the variables into five groups: fiscal variables, non-financial macroeconomic variables, financial variables, survey data, and interest rates. The variables are seasonally adjusted by implementing the TRAMO-SEATS method and converted into real log per capita levels when necessary. Appendix A lists the variables used as well as information about their source and characteristics.

The fiscal variables include total government spending, the government primary surplus divided by GDP, tax revenue, and the Barro-Redlick marginal tax rate. Total government expenditure is the federal plus state and local government consumption expenditure and gross investment. The marginal tax rate originally produced at an annual frequency by Barro and Redlick (2011) is extended to a quarterly frequency following Ellahie and Ricco (2017). Non-financial macroeconomic variables that reflect the macroeconomic and business conditions consist of real GDP, personal consumption expenditure, real gross private domestic investment, real wages, the unemployment rate, industrial production, housing starts, corporate profits after tax, the inflation rate, net exports divided by GDP and the real effective exchange rate from the Bank for International Settlements.

To control for the financial market conditions, our analysis also includes the following financial variables: the growth rate of the Standard & Poor (S&P) 500 stock market index, Baa/AAA spread, the AAA/10-year Treasury spread, liquidity premium measured as the difference between the synthetic off-the-run and on-the-run 10-year Treasury note yields and percentage changes in oil prices. To provide more information about agents' expectations, we include the consumer sentiment index developed by the University of Michigan and the Institute for Supply Management's New Orders Index and Inventories Index in the benchmark model. Following Forni and Gambetti (2016), we construct a *NEWS* variable, defined as the cumulative difference between the forecast of government spending growth at time t for the following three quarters and the forecast for the same quarters at time $t-1$ based on the data from the Greenbook's forecasts and the Survey of Professional Forecasters, to address fiscal foresight.

Except the effective federal funds rates, all the other interest rates are the zero-coupon yield data constructed by Gürkaynak et al. (2007). To decompose long-term interest rates, we use end-of-month observations from August 1971 to December 2018 on yields with maturities from one to 10 years.

4. Empirical results

4.1. Empirical algorithm

To implement the estimation and identification strategy discussed in Section 2, we follow three steps in the empirical exercise:

1. The first step is to estimate Eq. (13) in the large BVAR framework with $Y_t = \left[Z_t', F_t'\right]'$. In the following empirical exercise, we keep the variable in Z_t fixed and alter the variables in F_t for each experiment. We choose $p = 4$ and draw $n_1 = 5000$ random samples of $\left[B_+, \Sigma\right]$ from their posterior distributions.
2. The second step is the shock identification process. We take a random draw of $\left[\hat{B}_+, \hat{\Sigma}\right]$ from the n_1 samples constructed in the first step and then apply the sign-restriction method to identify q_s with $k = 1$ in the baseline specification. To implement the sign-restriction approach, we first use the QR decomposition method proposed by Rubio-Ramírez et al. (2010) to generate a candidate orthonormal vector q_s^0, and calculate the corresponding structural impulse response through $\psi_i^0 = \Theta_i \tilde{A} q_s^0,\ i = 1, \ldots, k$. Then, we compare the sign of each variable in ψ_i^0 with that in Table 1. If all the signs match, we stock q_s^0 and move on to identify the government spending news shock using the MFEV method with $H = 20$; if not, we discard it and proceed to another draw of $\left[\hat{B}_+, \hat{\Sigma}\right]$. We repeat this step until obtaining $n_2 = 2000$ admissible identification vectors.
3. We report the median as well as the 68% and 90% intervals of the posterior coverage of the empirical impulse responses.

4.2. Impulse response functions (IRFs)

In our baseline specification, we choose $F_t = [2-\text{year yields},\ 10-\text{year yields}]$. We identify the surprise shock using the sign-restriction method and the news shock using the MFEV approach. Fig. 1 reports the dynamic response of the selected macroeconomic variables to a positive government spending news shock.

[5] The length of the sample is determined by the data availability. In Appendix B.2, we also consider a larger data set with 46 quarterly series similar to the large VAR specification in Ellahie and Ricco (2017).

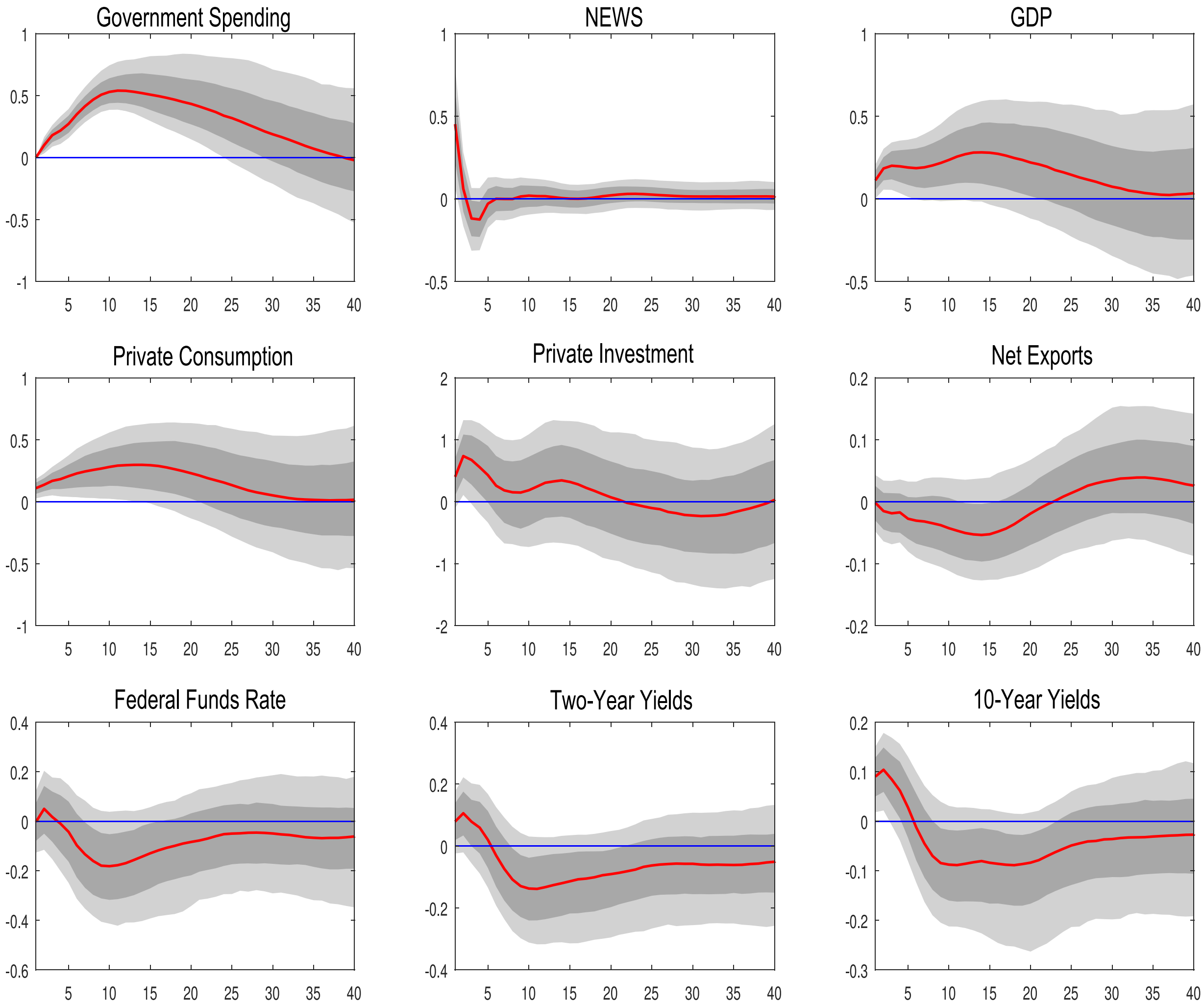

Fig. 1. Empirical impulse response of the identified government spending news shock under the baseline specification.
Note: Solid lines are the median response. Dark gray and light gray areas are the 68% and 90% posterior coverage intervals, respectively.

The news shock has a null effect on government spending on impact, which is consistent with the restriction in Eq. (19). In the subsequent period, government spending increases gradually, peaks after 11 quarters, and then decreases back to zero. The hump-shaped impulse response of government spending is similar to the finding in Ben Zeev and Pappa (2017) for defense spending news shocks except that the impulse response in our study is slightly more persistent probably because the other components of government expenditure emerge and show effects slower than defense spending. The news shock stimulates output (GDP) and crowds in both private consumption and investment significantly. These findings are qualitatively in line with those of Forni and Gambetti (2016) and Ben Zeev and Pappa (2017). Guo et al. (2015) show theoretically that output, consumption, and investment all increase after news about increases in government spending in a standard one-sector real business cycle model with variable capital utilization and mild increasing returns to scale. For the open economic variables, the trade balance deteriorates, but not significantly. Finally, two-year Treasury yields and 10-year Treasury yields behave in much the same way: they rise immediately and significantly on impact at least at the 68% level, and then decrease and become negative after about five quarters.[6]

As in Ben Zeev and Pappa (2017), to check whether our dynamic responses are reasonable from an economic perspective, we compute the government spending multiplier in the 11*th* quarter, when government spending peaks, as the 11-quarter

[6] We also investigate the effect of government spending news shocks on latent factors related to the yield curve. In the benchmark model, we find that the level and curvature factor rise in the impact period and decline gradually, whereas the slope factor does not exert a clear-cut response during the forecast horizons.

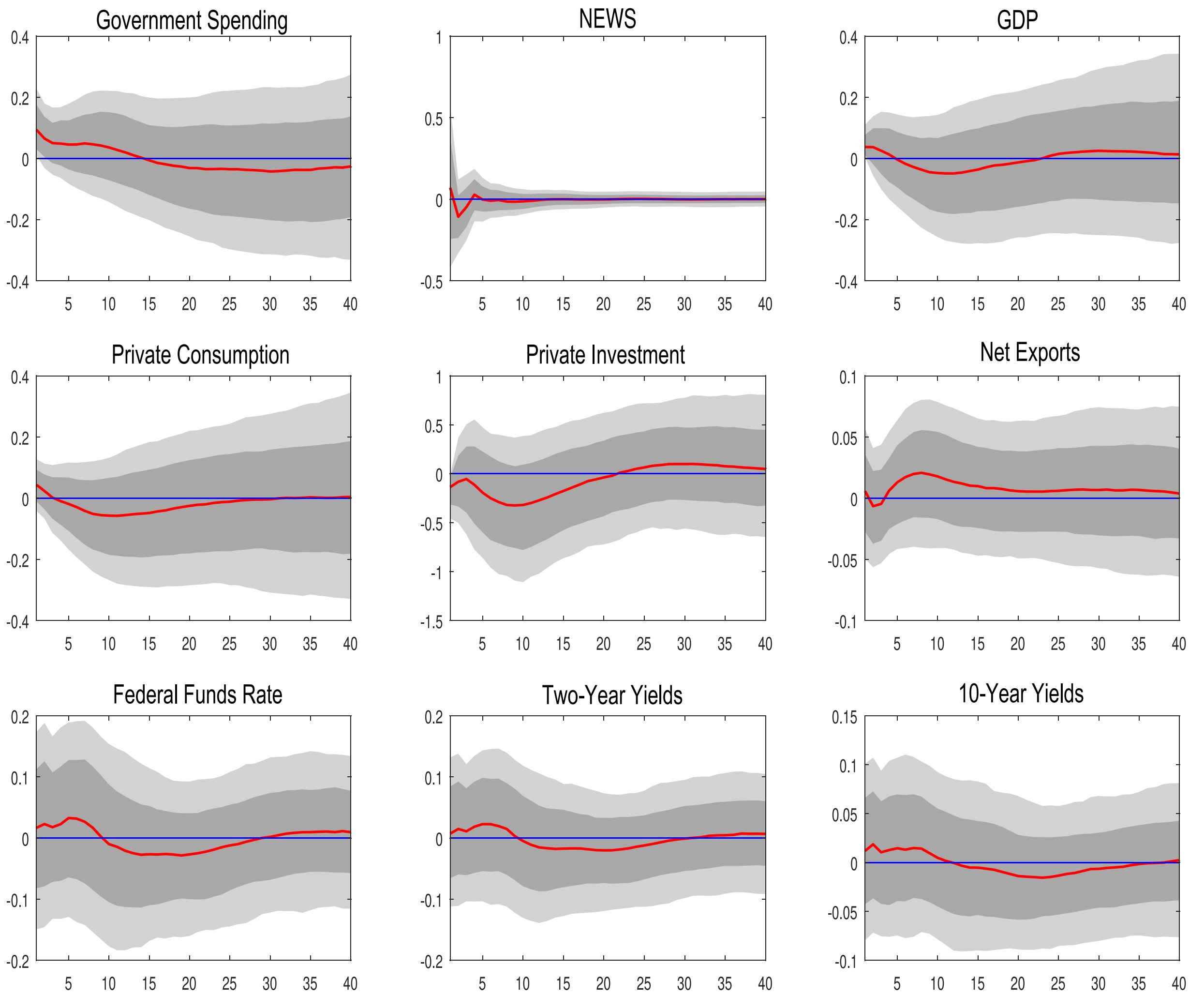

Fig. 2. Empirical impulse response of the identified government spending surprise shock under the baseline specification.
Note: See Fig. 1.

cumulative effect on output, divided by the 11-quarter cumulative effect on government spending multiplied by the average ratio of output to government spending over the sample period. In other words,

$$multiplier = \frac{\sum_{i=1}^{11} \log(Y_i)}{\sum_{i=1}^{11} \log(G_i)} \overline{\left(\frac{Y}{G}\right)}. \tag{22}$$

where Y is the level of output and G the level of government spending. In the baseline model, the cumulative output multiplier is 2.68, which is marginally larger than Ben Zeev and Pappa (2017) defense spending multiplier because of the more persistent response of government spending in our model.

Fig. 2 presents the IRFs to the positive government spending surprise shock. As we restrict only the signs of the responses in the impact period of the five variables shown in Table 1, their subsequent responses and the responses of the other variables are all what the data tell us. Government spending rises on impact, but the positive response is short-lived and subsides quickly. The short-lived response of government spending is also transmitted to output, consumption, and investment. Specifically, private consumption increases on impact. However, the positive government spending surprise shock does not lead to a significant response of both short- and long-term interest rates.

To explore the channels through which the government spending news shock affects long-term Treasury yields, we decompose 10-year yields into risk-neutral rates, which reflects expectations of future monetary policy and term premiums, which demonstrate the channel related to risk compensation. Following Evans and Marshall (2007), we fix Z_t in the VAR system, and substitute the interest rates in F_t with variables from the 10-year yield decomposition. Then, we re-estimate the VAR system and re-identify the anticipated and unanticipated government spending shocks.

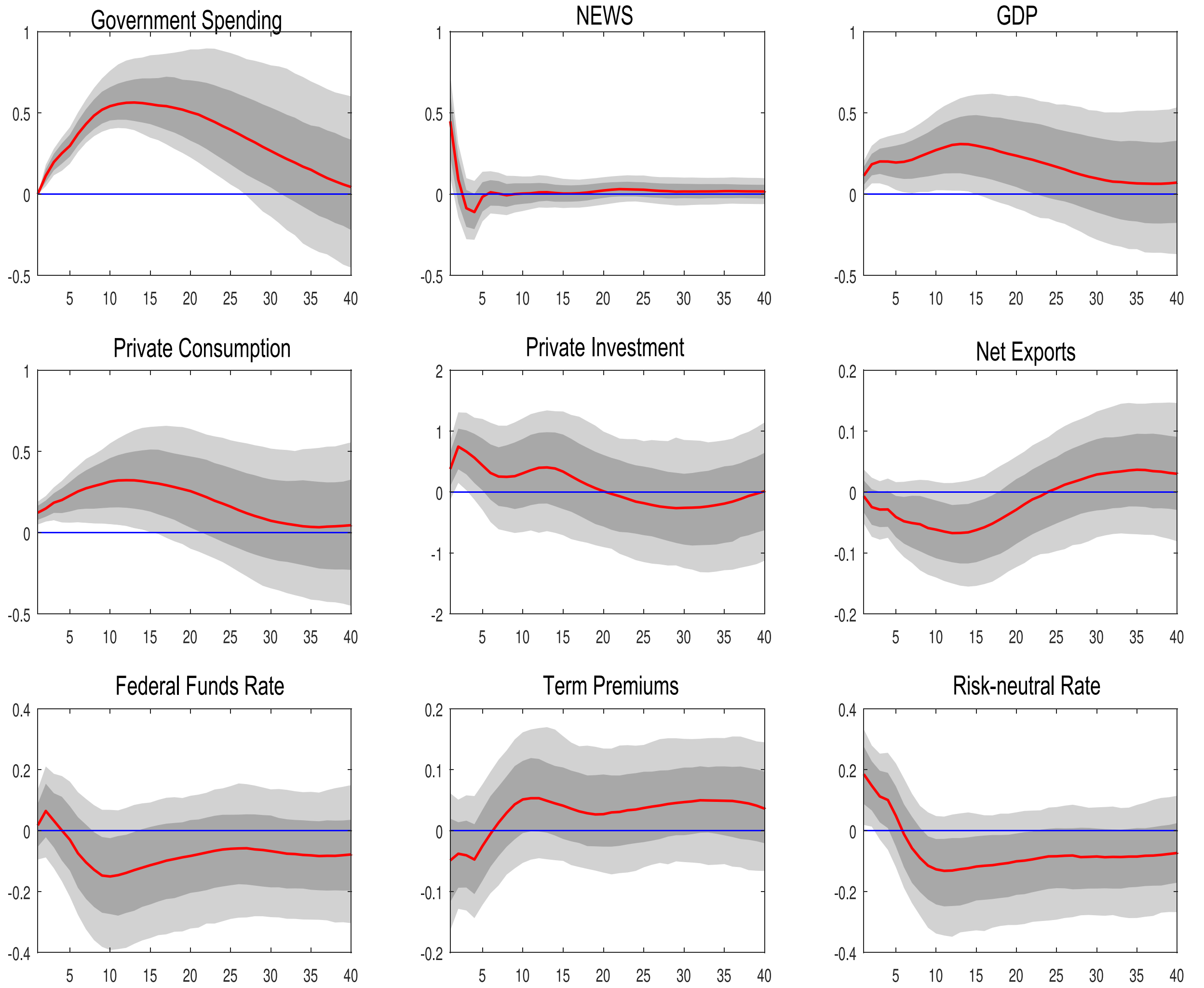

Fig. 3. Empirical impulse response of the identified government spending news shock by replacing the two-year yields and 10-year yields with the risk-neutral rates and term premiums by decomposing the 10-year yields.
Note: See Fig. 1.

Fig. 3 depicts the IRFs of the selected variables to the government spending news shock in this experiment. The patterns of the responses of the first seven variables are identical to those in Fig. 1. For the two variables related to the decomposition of the 10-year yields, we find that the dynamic path of the expected future short-term interest rates essentially tracts that of the 10-year yields. The response of term premiums, however, is different: it decreases on impact and remains negative in the subsequent seven quarters. Thus, we conclude that increases in 10-year U.S. Treasury yields after a positive government spending news shock are mainly caused by higher risk-neutral interest rates, which reflect expectations of future monetary policy.[7]

4.3. Comparison with different identification schemes

4.3.1. Recursive identification for both types of shocks

In the first exercise, we perform the recursive identification method proposed by Forni and Gambetti (2016) to identify unanticipated and anticipated government spending shocks. The government spending variable is ordered first in the VAR system following Blanchard and Perotti (2002) traditional VAR approach. The news variable (*NEWS*) which is constructed fol-

[7] We also find that 10-year inflation expectations rise after positive shocks to government spending news, which further supports the channel related to monetary policy expectations, while the effects of government spending news on inflation and 1-year inflation expectations are mixed.

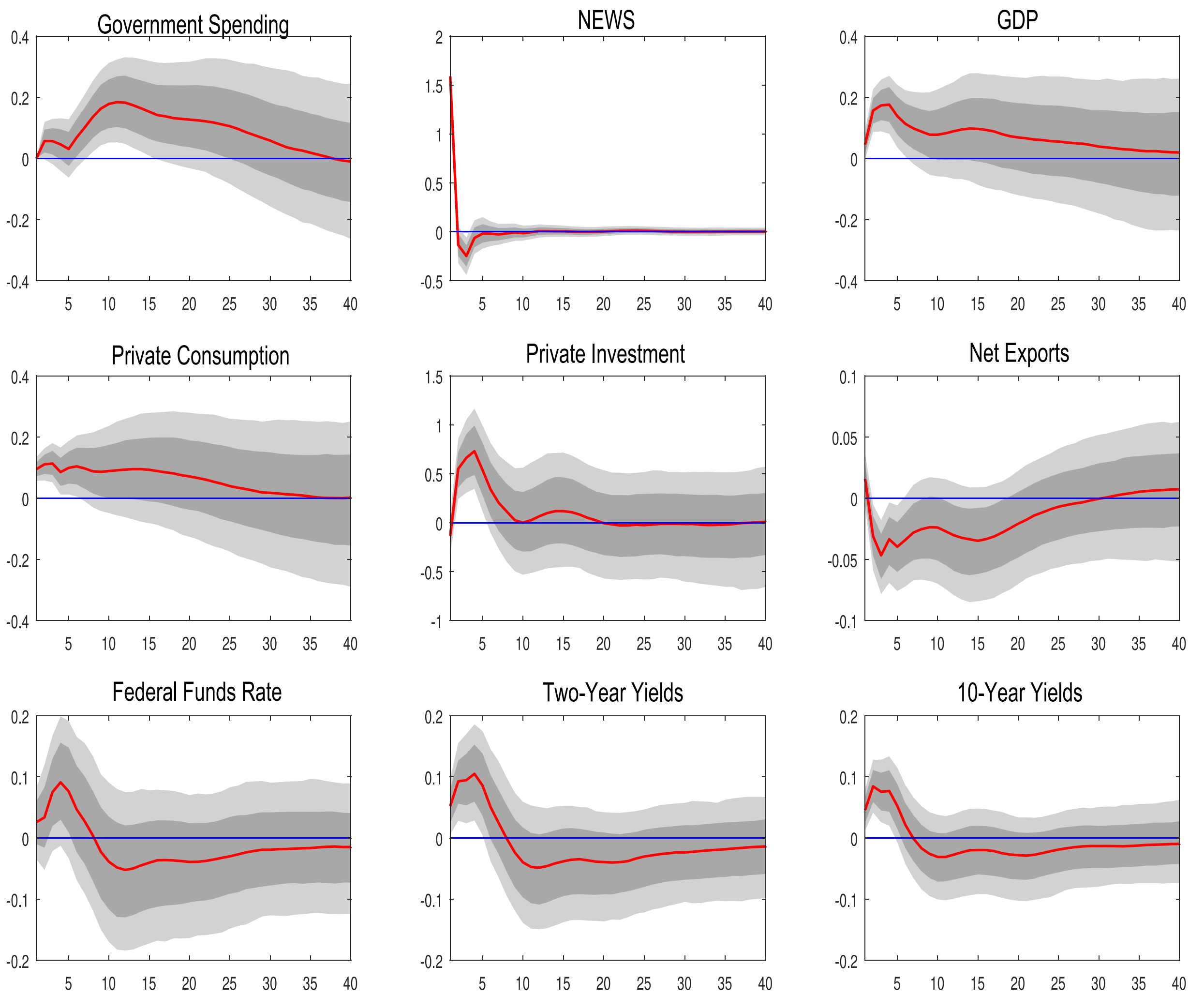

Fig. 4. Empirical impulse response of the news shock under the recursive identification scheme for both shocks.
Note: See Fig. 1.

lowing Forni and Gambetti (2016) is ordered second because under suitable assumptions (see Forni and Gambetti (2016) for a detailed explanation), the news variable convey only the current news shock and the lags of all the other shocks.

Fig. 4 illustrates the IRFs to the news shock of the selected variables under the recursive identification scheme. It is evident that the results from this exercise are mostly qualitatively similar to those in the benchmark model and Forni and Gambetti (2016). Compared with Fig. 1, there are also some quantitative differences that are worth mentioning: First, the government spending responses are a little bit less persistent than those in the benchmark model, which seems more plausible. Second, net export decreases significantly after a positive government spending news shock.

Fig. 5 shows the impulse response functions of selected variables to a positive government spending surprise shock. The results are similar to those in Forni and Gambetti (2016), but mostly different from those in the benchmark exercise. The short- and long-term interest rates decrease under recursive identification, while the responses are insignificant in the benchmark model.[8] In the following analysis, this study mainly focuses on government spending news shocks, whose effects are shown to be robust to the use of different identification schemes.

[8] The responses of long-term interest rates are sensitive to the sign assumptions related to federal funds rates. If we assume that an unanticipated increase in government spending induces an increase in federal funds rates as in some empirical studies, then long-term interest rates will rise after a positive government spending surprise shock.

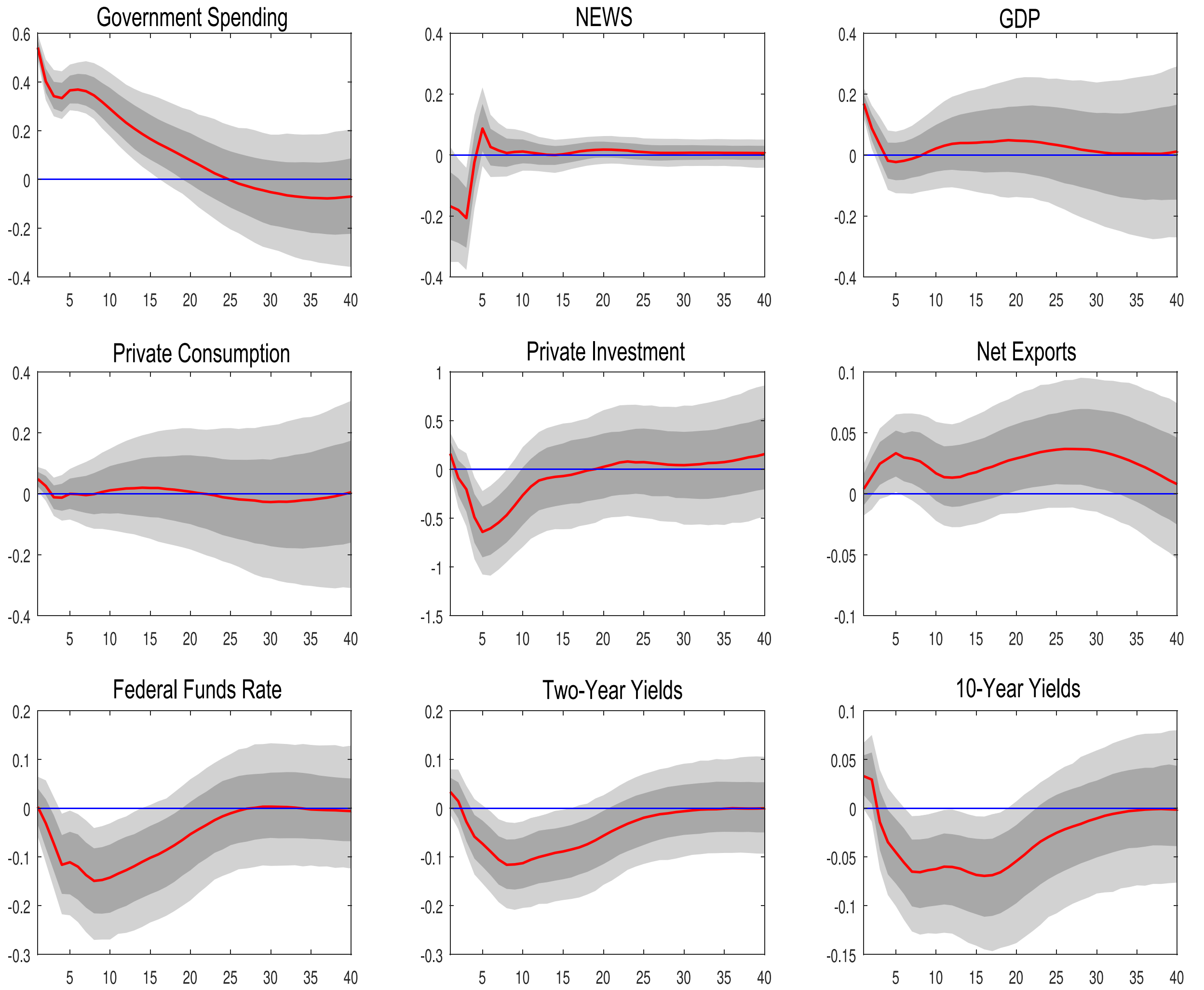

Fig. 5. Empirical impulse response of the surprise shock under the recursive identification scheme.
Note: See Fig. 1.

4.3.2. Recursive identification method for the surprise shock and the MFEV approach for the news shock

As in the previous studies such as Barsky and Sims (2011) and Ben Zeev and Pappa (2017) that use the MFEV approach to study news shocks, we use the recursive method to identify the surprise shock and MFEV method for the news shock to check the robustness of the identified government spending news shock in the benchmark model. To implement this combination, we fix q_s as the first column of the identity matrix I_n and re-solve the optimization problem in Eq. (18) to obtain q_n.

Fig. 6 reports the IRFs to the news shock obtained in this exercise, which behave similarly to those in the benchmark specification even though the government spending surprise shocks rely heavily on the identification schemes.

For the transmission channels related to the 10-year yields, Fig. 7 summarizes the impulse responses of the term premium and risk-neutral rate to the news shock under both alternative identification schemes. Under both identification schemes, the responses are qualitatively similar to the benchmark results in Fig. 3: the risk-neutral rate tracks the path of the 10-year yields, and the risk premium behaves differently.

4.4. Estimated government spending news shocks

In this subsection, we analyze the information content of the estimated government spending news shocks in our benchmark specification and compare it with the *NEWS* variable and news shocks based on Forni and Gambetti (2016). Fig. 8 plots the three series and vertical lines associated with important historical events such as legislative acts and war episodes. Positive (negative) values mean that expectations about future government spending are revised upward (downward).

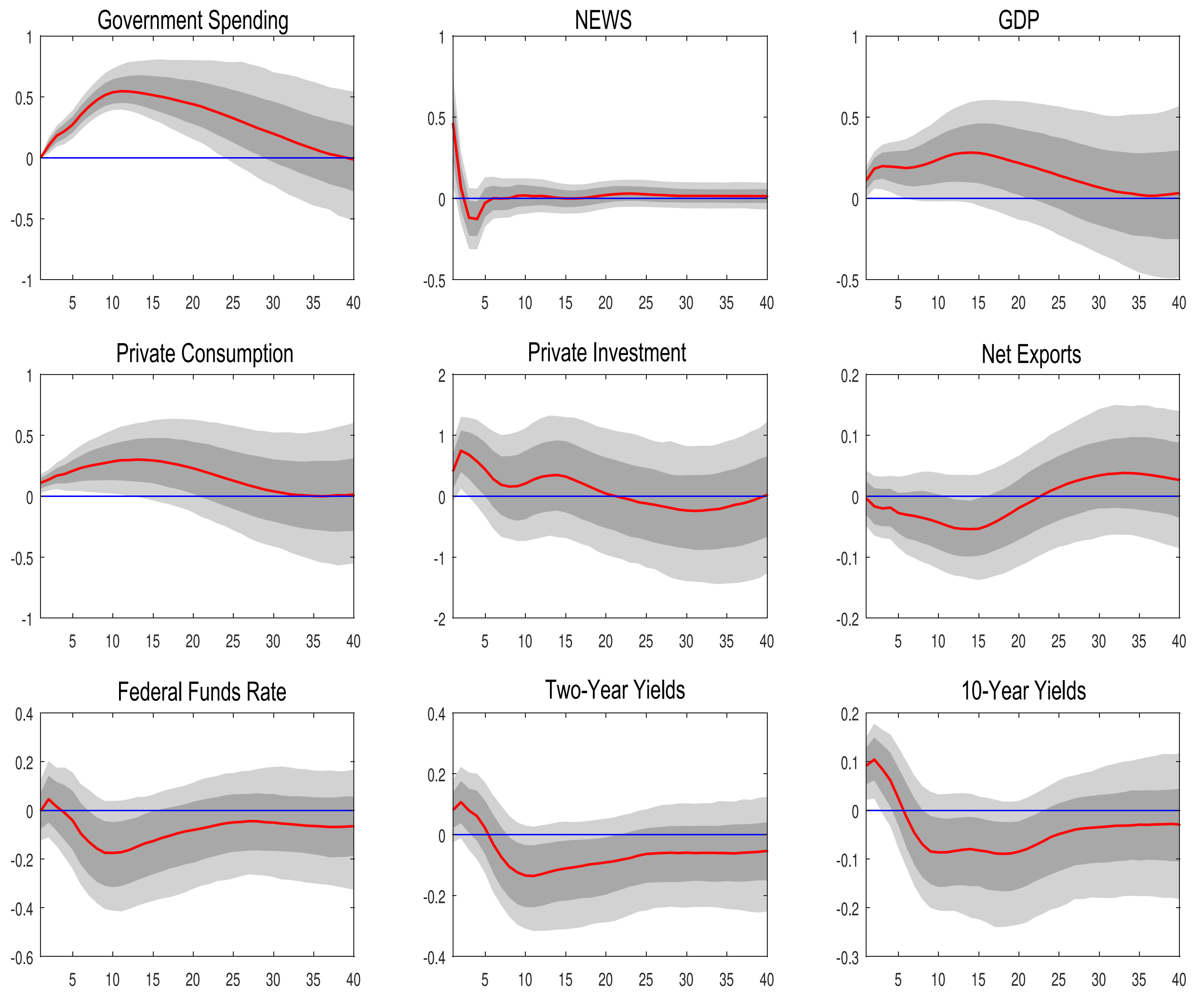

Fig. 6. Empirical impulse response of the news shock under the recursive identification scheme for a surprise shock and under the MFEV approach for a news shock. *Note*: See Fig. 1.

After consecutive budget deficits and a massive increase in the national debt in the early 1980s, a series of legislative acts balanced the budget through spending cuts. The Balanced Budget and Emergency Deficit Control Act of 1985, known as "Gramm-Rudman-Hollings," was the first that provided for automatic spending cuts if the deficit exceeded a set of fixed deficit targets. The 1985 law was ruled unconstitutional in the case of Bowsher v. Synar in 1986 and Congress enacted a reworked version of the law in 1987, known as "Gramm-Rudman-Hollings II." However, to avoid spending cuts, policymakers started using overly optimistic budget projections, which made "Gramm-Rudman-Hollings" fail to prevent large budget deficits. The Budget Enforcement Act of 1990 supplanted the fixed deficit targets, created caps for discretionary spending, and established the pay-as-you-go (PAYGO) system, which required that any new spending increase or tax cut must be offset by spending cuts or tax increases elsewhere. The Budget Enforcement Act of 1990 was extended by the Deficit Reduction Act of 1993, and again by the Balanced Budget Act of 1997, but expired in 2002. After the financial crisis of 2008, which increases U.S. debt rapidly, the PAYGO system was reestablished as a standing rule of the House of Representatives in 2007, which was in the end reinstated by the Statutory Pay-As-You-Go Act of 2010. Discretionary spending caps as well as deficit reduction targets were reintroduced by the Budget Control Act of 2011.

Our benchmark news shocks display negative spikes in tandem with all seven of the legislative activities mentioned above except the Balanced Budget Act of 1997. All three series assign a positive value for the third quarter of 1997 when the Balanced Budget Act of 1997 was signed into law. As the U.S. economy was growing at a rapid pace at that time, this increased federal revenues markedly. Both Democrats and Republicans saw a federal budget surplus on the horizon in 1997,

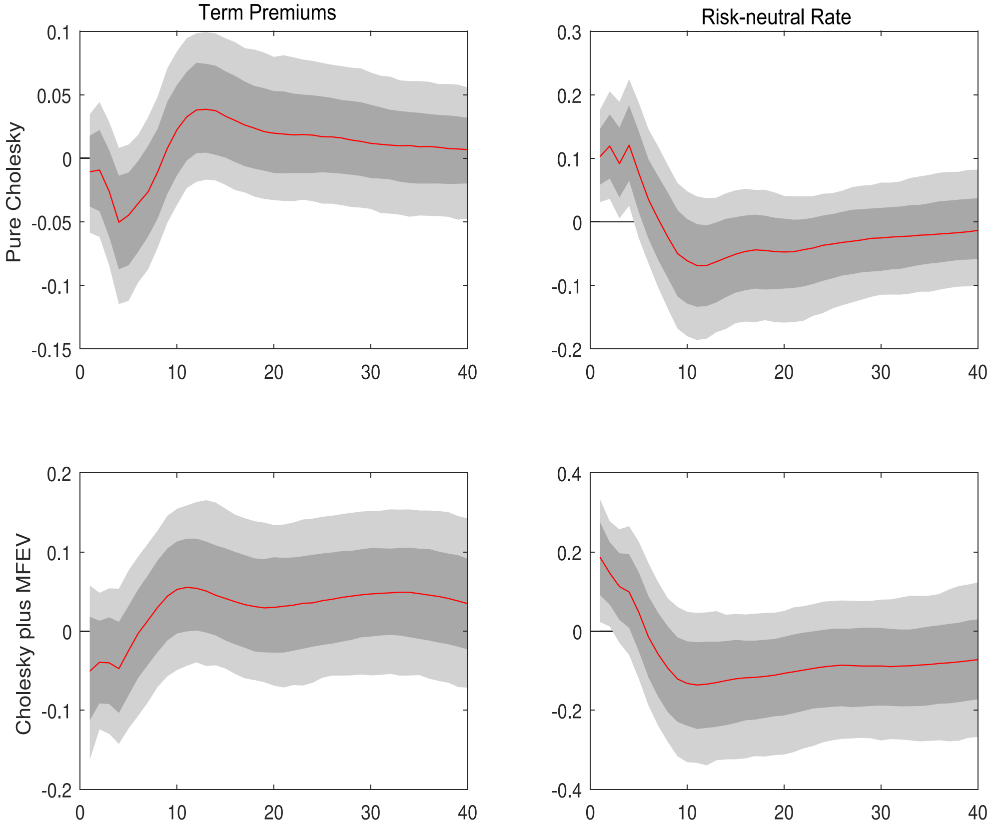

Fig. 7. Empirical impulse response of term premium and risk neutral rate to news shock under alternative identification scheme. *Note*: See Fig. 1.

which mitigated the problem of balancing the budget and reduced the negative impact of the act on spending.[9] Compared with the MFEV series, the *NEWS* variable and news shocks based on Forni and Gambetti (2016) both fail to capture the Deficit Reduction Act of 1993, the re-established PAYGO system in 2007 and the Budget Control Act of 2011.

Fig. 8 lists four important events related to changes in defense spending. Since we investigate expectations of changes in aggregate government spending, changes in non-defense spending might offset the impact of changes in defense spending. For example, the Budget Enforcement Act of 1990 makes all three series assign a negative value to the third quarter of 1990 when the First Gulf War broke out. For the Second Gulf War in 2003Q1, our estimated news shocks have a positive value one quarter later than the Ramey (2011) narrative defense shocks, but match the Ramey (2011) news shocks in 2003Q3. Ultimately, all the remaining events listed in Fig. 8 are well captured by our benchmark news shocks except that the change in 2009Q1 related to Obama's fiscal stimulus package is not large enough in the benchmark series.

To conclude, the correlation between the benchmark news shocks based on the MFEV approach and the news shocks based on Forni and Gambetti (2016) is 0.4, which demonstrates that these two series have much in common even though they are extracted using different identification approaches. Moreover, the MFEV series is recovered using information not only from the *NEWS* variable but also from exploiting the forecast error variance decomposition of government spending. This allows it to successfully identify several important legislative activities in U.S. history, which the news shocks based on Forni and Gambetti (2016) fail to capture. If not better than the other two series in Fig. 8, our estimated government spending news shocks at least contain valuable information on changes in government spending.[10]

[9] In fact, beginning in 1998, in response to the first federal budget surplus since 1969, Congress started enacting increases in discretionary spending above the statutory limit.

[10] We consider a VAR system excluding the *NEWS* variable in Appendix B.1. The correlation of the MFEV news shocks without using the *NEWS* series and the benchmark shocks is 0.92, which indicates that the *NEWS* variable adds little information into our VAR system and that the effects of government spending news shocks can be well estimated even without the information from professional forecasters. A detailed discussion can be found in Appendix B.1.

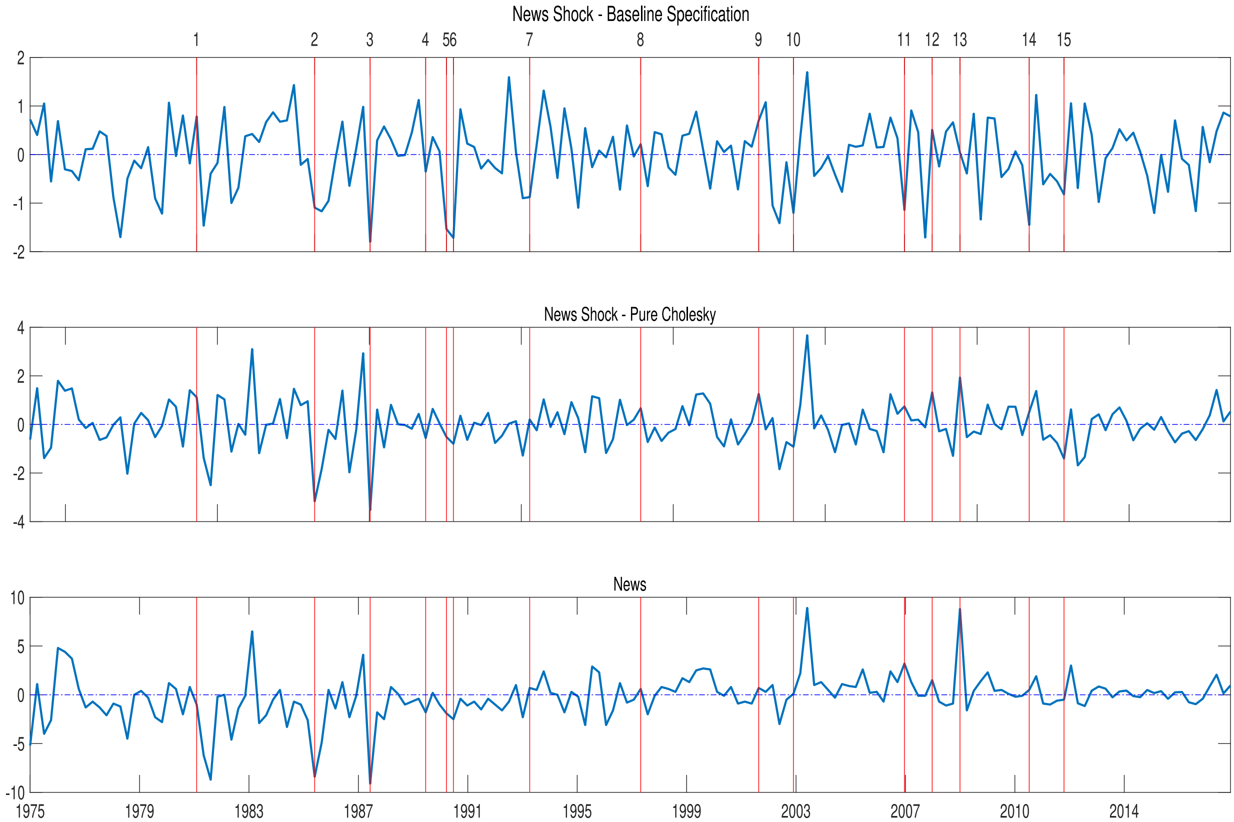

Fig. 8. Top panel: News shock under the baseline specification; Mid panel: News shock under the Cholesky identification; Bottom panel: Spending news variable (*NEWS*). *Note*: The vertical lines are associated with the following episodes:(1)1981Q3 Gramm-Latta II (the Omnibus Budget Reconciliation Act of 1981); (2)1985Q4 Gramm-Rudman-Hollings (Balanced Budget and Emergency Deficit Control Act of 1985); (3)1987Q4 Gramm-Rudman-Hollings II (Balanced Budget and Emergency Deficit Control Reaffirmation Act of 1987); (4) 1989Q4 Fall of the Berlin Wall; (5) 1990Q3 Gulf War; (6) 1990Q4 The Budget Enforcement Act of 1990; (7) 1993Q3 The Deficit Reduction Act of 1993 (The Omnibus Budget Reconciliation Act of 1993); (8) 1997Q3 The Balanced Budget Act of 1997; (9) 2001Q4 War in Afghanistan; (10) 2003Q1 Second Gulf War; (11) 2007Q1 Reestablished PAYGO; (12) 2008Q1 2008 fiscal stimulus (Economic Stimulus Act of 2008); (13) 2009Q1 Obama fiscal stimulus (American Recovery and Reinvestment Act of 2009); (14) 2011Q3 The Budget Control Act of 2011; (15) 2012Q4 Fiscal cliff.

4.5. Variance decomposition

We construct variance decompositions to gauge the relative contributions of government spending shocks to the fluctuations in the 10-year Treasury yield and its decomposition. Table 2 summarizes the medium forecast error variance decompositions of the government spending news shocks and government spending surprise shocks for 24 quarters under all three identification schemes.

Under all the identification specifications, the forecast error variance decomposition results indicate that a news shock is more important than a surprise shock in explaining variations in 10-year Treasury yields and their decomposition for most forecast horizons (except for the recursive identification scheme, under which the result holds for the first two years), suggesting that a more important role is played by the government spending news shock in shaping fluctuations in long-run yields and their components. The forecast error variance decomposition variance of 10-year yields related to surprise shocks is quite small, which is stable at around 3% over 24 quarters. However, the proportion of the volatility in long-run rates explained by the MFEV news shock is steady at around 10%. In addition, the news shock exerts higher explanatory power for the fluctuation in the risk-neutral rate than for that of the term premiums for all the forecast horizons and all the model specifications, which is in line with our conclusion that the expected future short-term interest rates facilitate the transmission of the news shock to long-term yields.

To examine whether the above differences in explanatory power between news and surprise shocks are statistically significant, we use the Wilcoxon signed-rank test to compare the means of the contribution of the MFEV news shock and the sign-restriction surprise shock to the variation in 10-year yields. We estimate the p-value for the null hypothesis that the differences between the contribution of the MFEV news shock and sign-restriction surprise shock to the variation in 10-year yields is no larger than zero. The estimated p-values in all the forecast periods are close to 0, indicating that the null hy-

Table 2
Variance decomposition.

Variables	Share of FEV attribute to news shocks					Share of FEV attribute to surprise shocks				
	$h=1$	$h=4$	$h=8$	$h=12$	$h=24$	$h=1$	$h=4$	$h=8$	$h=12$	$h=24$
Baseline specification										
10-year yields	9.75	9.61	8.13	9.79	11.30	1.56	2.15	2.30	2.38	2.57
Term premiums	2.17	3.17	3.86	5.64	6.56	1.78	2.22	2.35	2.74	2.78
Risk-neutral rate	8.54	8.21	7.08	8.64	10.25	1.48	2.05	2.26	2.45	2.77
Recursive identification for both shocks										
10-year yields	2.48	6.53	4.20	3.70	3.38	1.29	1.66	3.06	3.95	4.93
Term premiums	0.25	1.33	1.80	2.46	2.60	0.46	1.32	3.04	4.35	3.70
Risk-neutral rate	2.55	4.89	3.50	3.71	3.74	0.39	1.38	3.67	5.23	5.50
Recursive identification for a surprise shock and MFEV approach for a news shock										
10-year yields	9.90	9.85	8.16	9.85	11.60					
Term premiums	2.14	3.05	3.78	5.52	6.43					
Risk-neutral rate	8.53	8.12	7.03	8.93	10.72					

Note: Percentage of the forecast error variance explained by the news and surprise shocks at different horizons.

Table 3
Results of the fundamentalness test for the news shock. *Note*: Each entry of the table denotes the p-value of the F-test in a regression of the news shock estimated in the benchmark model on the lags of the first-difference principle components.

No. of lags (K)	No. of principal components (N)									
	1	2	3	4	5	6	7	8	9	10
1	0.70	0.91	0.97	0.97	0.94	0.92	0.92	0.96	0.93	0.95
2	0.46	0.66	0.86	0.93	0.95	0.77	0.88	0.78	0.60	0.66
3	0.68	0.85	0.94	0.95	0.99	0.77	0.88	0.81	0.38	0.44
4	0.73	0.94	0.98	0.99	0.99	0.84	0.94	0.60	0.43	0.35

pothesis is rejected at the 1% level and that our news shock is more important in explaining the fluctuation in long-term yields. Applying the same method, the result that the news shock exerts higher explanatory power for the fluctuation in the risk-neutral rate than for that of the term premiums is also statistically significant.

4.6. Robustness checks

4.6.1. Informational sufficiency

To verify whether the government spending news shock identified in our baseline VAR suffers from the problem of informational insufficiency, we use the orthogonality test proposed by Forni and Gambetti (2014). Specifically, we follow Forni et al. (2014) and perform the following steps. We first extract 10 principal components f_t^n, $n = 1, \dots, 10$ from an even larger data set to approximate the information flow in the economy[11] and then run the following regression:

$$u_t^n = \alpha + \sum_{n=1}^{N}\sum_{k=1}^{K} \beta_k^n \, \Delta f_{t-k}^n + e_t, \tag{23}$$

where u_t^n is the median of the news shock identified from the baseline specification, Δf_t^n is the first difference of the principal components, and $K = 1, \dots, 4$, $N = 1, \dots, 10$. Finally, we test for the orthogonality of the estimated shock with respect to the lags of principal components in first differences using a standard F-test. The null of fundamentalness (informational sufficiency) is rejected if and only if orthogonality is rejected.

Table 3 reports the p-values of the F-test for a different set of principal components (columns) and different lags (rows). In all the specifications, orthogonality clearly cannot be rejected at the 5% level, which verifies that the information in our data set is sufficient.

4.6.2. Sub-sample stability

The 2007–2008 financial crisis that began to emerge in 2007Q3 made the U.S. economy hit the zero lower bound on interest rates from 2008Q4. To check whether our baseline results are sensitive to the financial crisis and zero lower bound periods, we truncate our sample to the period 1974Q3 − 2007Q2. We re-estimate the VAR system with this smaller sample

[11] The data set is taken from the FRED-QD database, which includes 235 variables during the sample period.

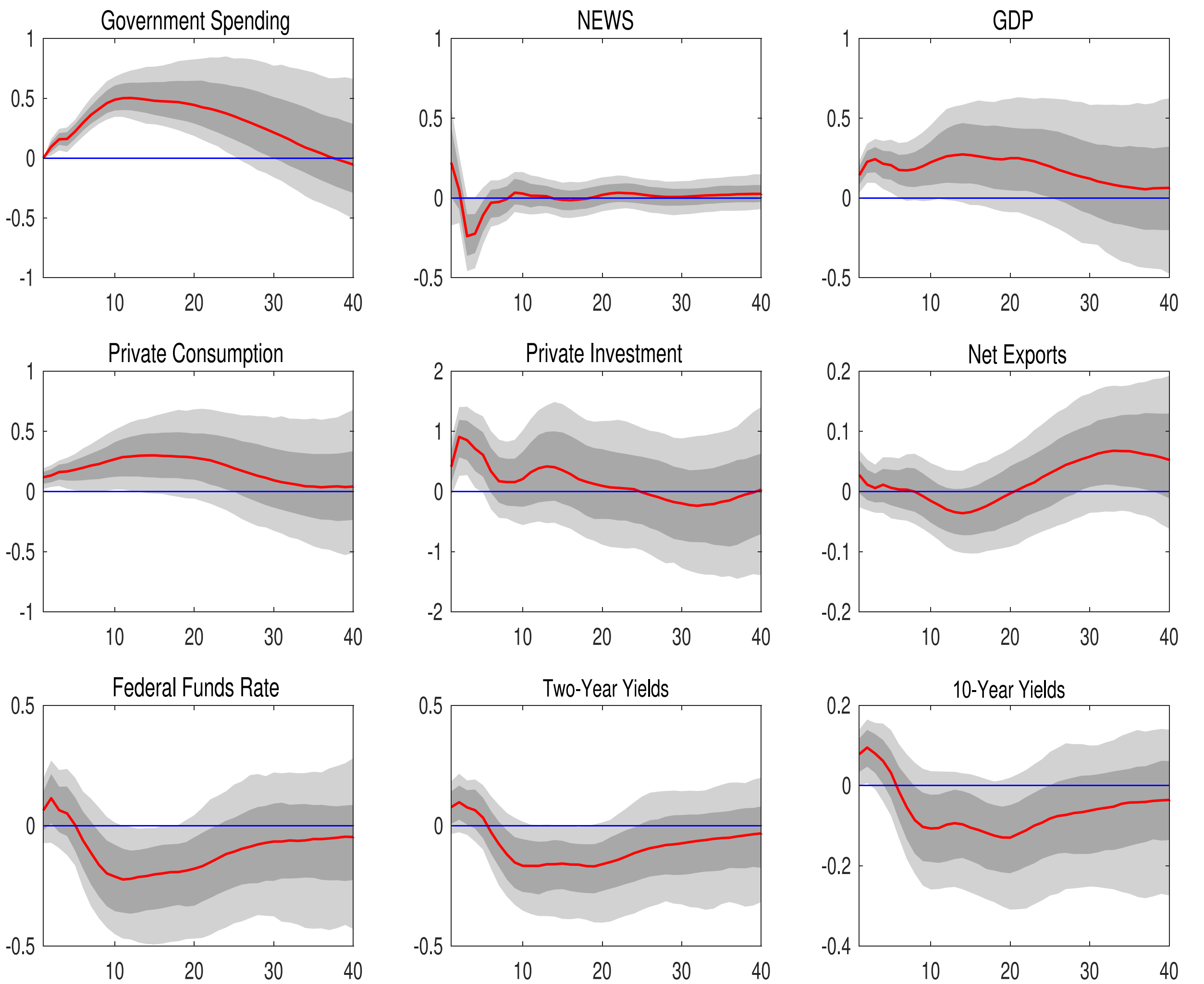

Fig. 9. Empirical impulse response of the identified government spending news shock in the sub-sample 1974Q3 – 2007Q2. *Note*: See Fig. 1.

and re-identify the government spending news and surprise shocks. Fig. 9 illustrates the results, showing that news about increases in government spending induces increases in both 2-year and 10-year Treasury yields.[12]

4.6.3. Assuming that a news shock affects government spending four quarters later

In our baseline specification, as shown in Eq. (19), we assume that news shocks affect government spending with a one-quarter delay due to legislative and implementation lags; in other words, a news shock occurring in quarter t is assumed to affect government spending in quarter $t+1$. In this robustness exercise, we take into account the possibility that legislative and implementation lags for fiscal policy are longer than a quarter and verify the robustness of our baseline results for the case in which a news shock occurring in quarter t affects government spending in quarter $t+4$. Specifically, we substitute Eq. (19) with

$$\tilde{\Xi}_i(1,:)\, q_n = 0, \quad i = 1, \ldots, 4, \tag{24}$$

and resolve the MFEV problem to find q_n, where $\tilde{\Xi}_i(1,:)$ is the first row of the Cholesky impulse response (i.e., $\tilde{\Xi}_i = \Theta_i \tilde{A}$ and $\tilde{A}$ is the lower triangular Cholesky decomposition of Σ) at horizon i.

Fig. 10 plots the impulse response. With the exception of government spending, all the other variables behave almost identically to the baseline results (see Fig. 1) over all horizons, especially in the first four quarters when government spend-

[12] In the robustness checks, we do not present the results related to the decomposition of interest rates as they are similar to the benchmark results: however, they are available upon request.

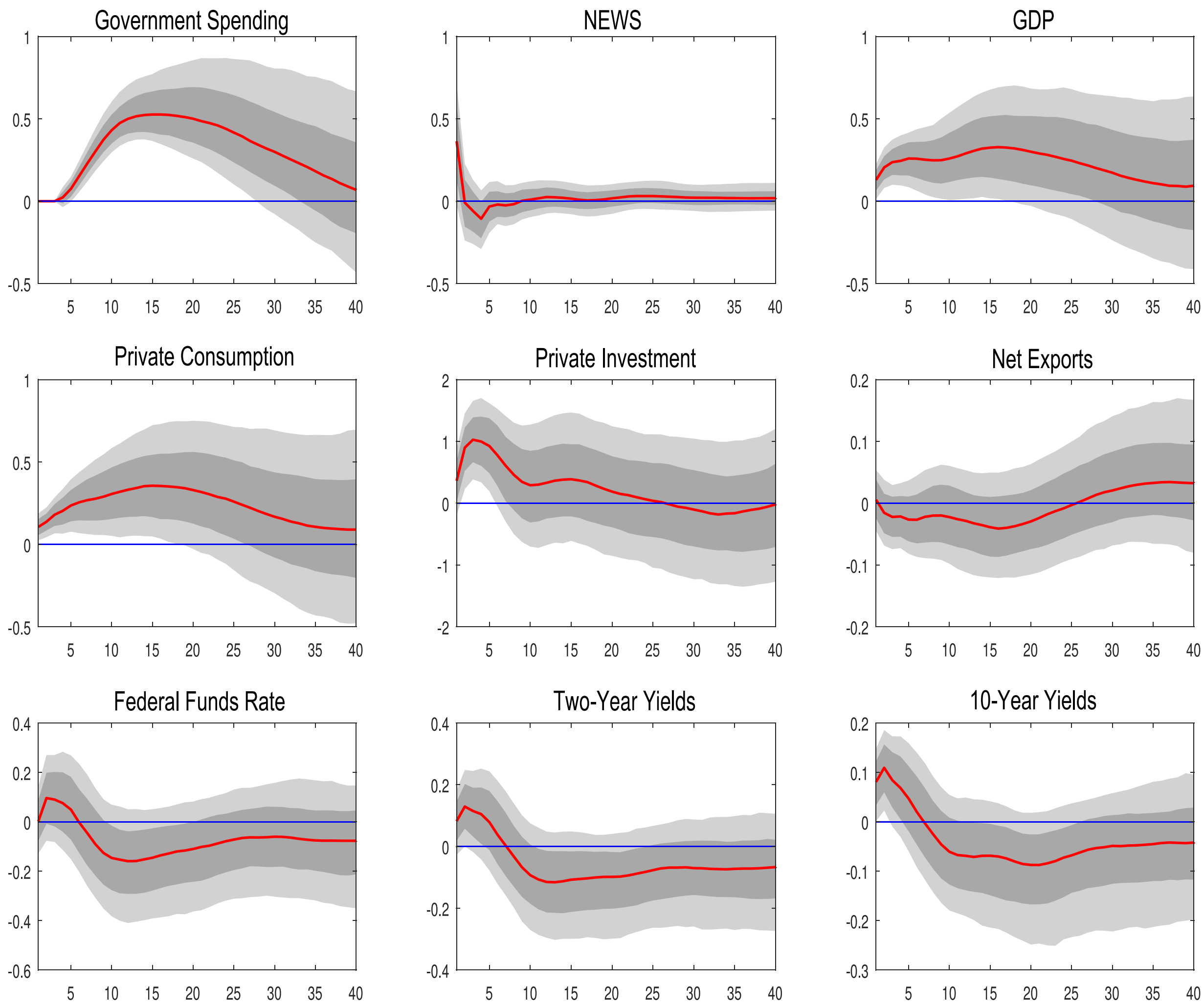

Fig. 10. Empirical impulse response of the identified government spending news shock by assuming that a news shock affects government spending four quarters later. *Note*: See Fig. 1.

ing does not respond to news shocks by construction. Therefore, our baseline results are not sensitive to the assumption about the length of legislative and implementation lags.

4.6.4. Monetary policy shocks

Changes in monetary policies may contribute considerably to changes in long-term interest rates and their decomposition. Thus, in this subsection, we investigate whether the results obtained under our baseline specification are sensitive to a modification where we explicitly identify monetary policy shocks. In practice, we identify government spending surprise shock q_s and monetary policy shock q_m using a sign restriction approach (see Table 1). Defining the matrix $Q_s = [q_s, q_m]$, we change the second restriction, namely Eq. (20) in the MFEV approach to

$$Q_s' q_n = 0, \tag{25}$$

and resolve the MFEV problem to find government spending news shock q_n. Eq. (25) indicates that the government spending news shock is orthogonal to both the surprise shock and monetary policy shock. The impulse responses to the government spending news and surprise shocks are almost the same as the benchmark case presented in Figs. 1 and 2; these results are available upon request.

4.6.5. Other robustness checks

In addition to the exercises discussed above, we examine the robustness of the results under the benchmark specification along the following dimensions: (i) we assume different lag specifications in the benchmark VAR or alternative truncation horizons for the MFEV optimization problem; (ii) we change the number of periods for the sign restriction from $k = 1$ to $k = 4$ when we identify the government spending surprise shocks; (iii) we assume that business cycle shocks can affect the government spending process; (iv) we exclude the *NEWS* variable from the benchmark VAR; (v) we add more variables into the benchmark VAR; and (vi) we identify government spending surprise shocks using the proxy SVAR approach.

The results of the first three checks differ little from the benchmark results, and therefore are not presented to save space. The results of the last three checks, which are shown in Appendix B, also indicate that our main results are robust.

5. Conclusion

In this study, we employ large BVAR models with full information which overcome issues of fiscal foresight, to investigate the effect of news about government spending on U.S. Treasury yields. Following Barsky and Sims (2011) and Francis et al. (2014), we identify news shocks to U.S. government spending as the shocks that best explain future movements in government spending over a 20-quarter horizon and are orthogonal to government spending surprise shocks, which are identified using sign restrictions. We find that positive government spending news shocks significantly increase both short- and long-term interest rates, which are robust under different specifications and identification schemes. Previous studies such as Evans and Marshall (2007) find little empirical evidence that fiscal policy shocks are an important source of interest rate variability. However, this work shows that because of fiscal foresight, a fiscal policy shock does not display the effect at the time at which government expenditure is effectively realized but rather a few periods after it is announced. In addition, government spending news shocks can explain 10% of the fluctuations in 10-year Treasury yields, which is much larger than government spending surprise shocks.

Using the empirical dynamic term structural models proposed by Bauer et al. (2012), we further decompose changes in long-term interest rates into changes in risk-neutral interest rates and changes in term premiums to explore the channels through which news about government spending affects long-term interest rates. We find that government spending news shocks affect 10-year Treasury yields mainly through expectations of future monetary policy.

These results have two policy implications. First, anticipation effects are important when studying fiscal policy. Policymakers should be cautious in announcing policy changes that can affect agents' expectations of future government spending. Second, changes in agents' expectations of future government spending play an important role in shaping expectations of future monetary policy, which demonstrates the importance of the coordination between fiscal and monetary policy communication.

Appendix A. Data definitions and sources

- Fiscal variables(4):
  1. Government spending: Federal plus state and local government consumption expenditure and gross investment, Source: Bureau of Economic Analysis.
  2. Primary surplus: Government net saving minus income receipt on asset, interest and miscellaneous plus interest payment, expressed as a percentage of gross domestic product, Source: Bureau of Economic Analysis.
  3. Tax revenue: Government tax receipts plus contributions for government social insurance minus government transfer payments receipts, Source: Bureau of Economic Analysis.
  4. Marginal tax rate: Marginal tax rate from Barro and Redlick (2011) which is extended and converted to a quarterly frequency following Ellahie and Ricco (2017).
- Non-financial macroeconomic variables (11):
  1. Output: Real gross domestic product, Item: GDPC96, Source: FRED.
  2. Private consumption: Real personal consumption expenditures, Source: Bureau of Economic Analysis.
  3. Private investment: Real gross private domestic investment, Item: GPDIC96, Source: FRED.
  4. Real wage: Real compensation per hour in business sectors, Item: RCPHBS, Source: FRED.
  5. Unemployment rate: Civilian unemployment rate, Item:UNRATE, Source: FRED.
  6. Industrial production: Industrial production index, Item:INDPRO, Source: FRED.
  7. Housing start: Total new privately owned housing units started, Item: HOUST, Source: FRED.
  8. Corporate profits after tax: Corporate profits after tax with inventory valuation adjustment and capital consumption adjustment, Item:CPATAX, Source:FRED.
  9. Inflation rate: Personal consumption expenditures chain-type price index (Percent Change), Item: PCECTPI, Source: FRED.
  10. Net export: Net export as a percentage of gross domestic product, Source: FRED.
  11. Real exchange rate: BIS real effective exchange rate (narrow indices), Source: Bank of International Settlement.
- Financial variables (5):
  1. S&P 500: S&P 500 Stock Market Index (Percent Change), Item: SP500, Source: FRED.

2. Baa/AAA spread: Moody's seasoned Baa corporate bond yield minus Moody's seasoned AAA corporate bond yield, Source: FRED.
3. AAA/10-year Treasury spread: Moody's seasoned AAA corporate bond yield minus 10-year zero-coupon Treasury yields, Source: FRED.
4. Liquidity premium: Difference between par-coupon yields of seasoned 10-year Treasury bonds (as in Gürkaynak et al. (2007)) and the yield on newly issued 10-year Treasury bonds (as reported in the Federal Reserve s H.15 series).
5. Oil price: Spot West Texas Intermediate crude oil price (Percent Change), Item: WTISPLC, Source: FRED.

- Survey data (4):
  1. Consumer sentiment index: Consumer sentiment index by University of Michigan, Item: UMCSENT, Source: FRED.
  2. New orders index: ISM manufacturing new orders index, Source: the Institute of Supply Management.
  3. Inventory index: ISM manufacturing inventory index, Source: the Institute of Supply Management.
  4. NEWS: The cumulative difference between the forecast of government spending growth made at time t for the following three quarters and the forecast for the same quarters made at time $t-1$ as defined in Forni and Gambetti (2016). The data from 1974 ro 2012 is from the Greenbook Data Set. We extend the data series to 2018 by aggregating growth forecasts of federal expenditures and state and local expenditures under the assumption that price levels for these two types of government expenditures are the same since 2012. Source: Philadelphia Fed's Greenbook Data Set and the Survey of Professional Forecasters.
- Interest rates and population:

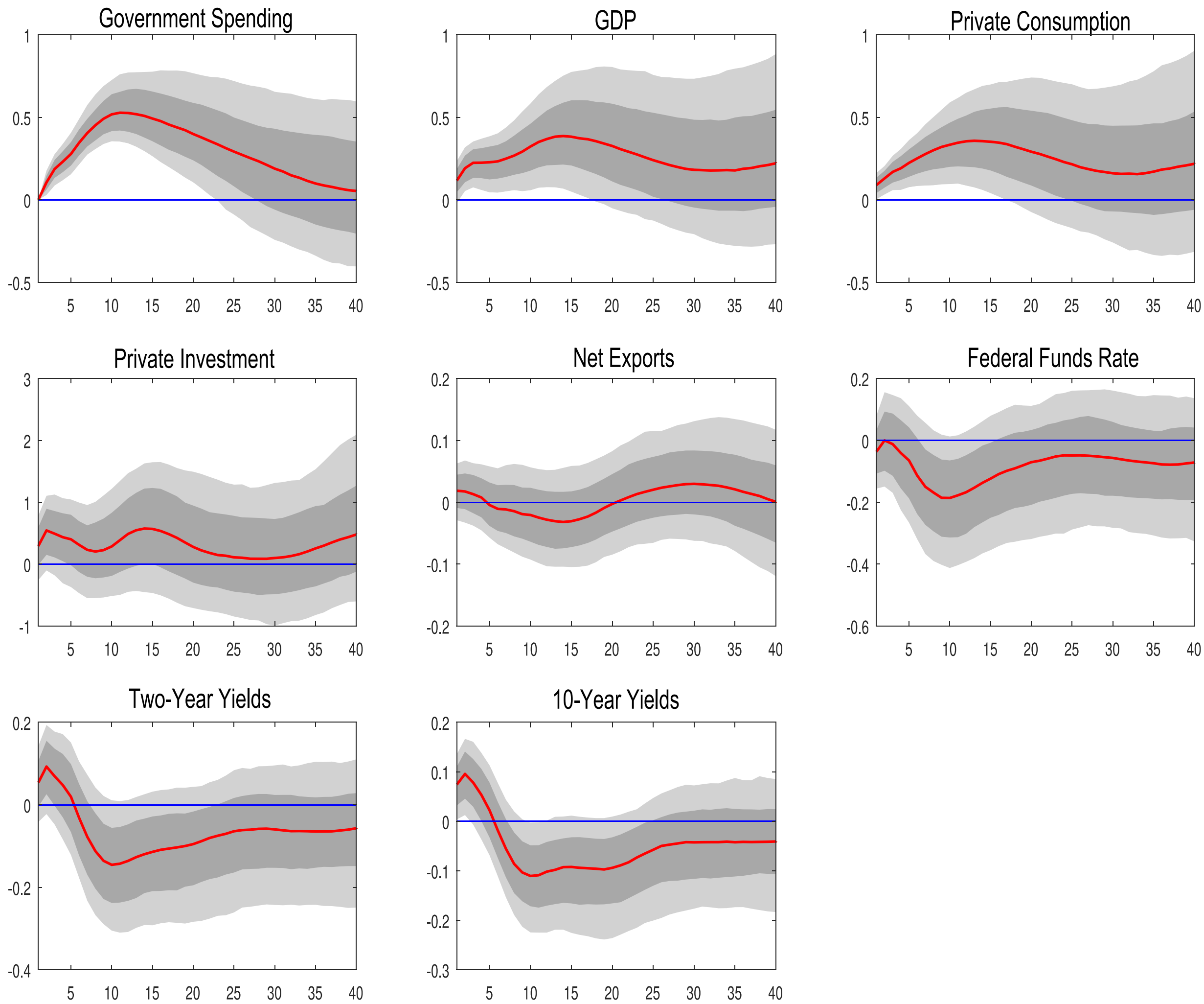

Fig. B.1. Empirical impulse response of the identified government spending news shock without the *NEWS* variable.
Note: See Fig. 1.

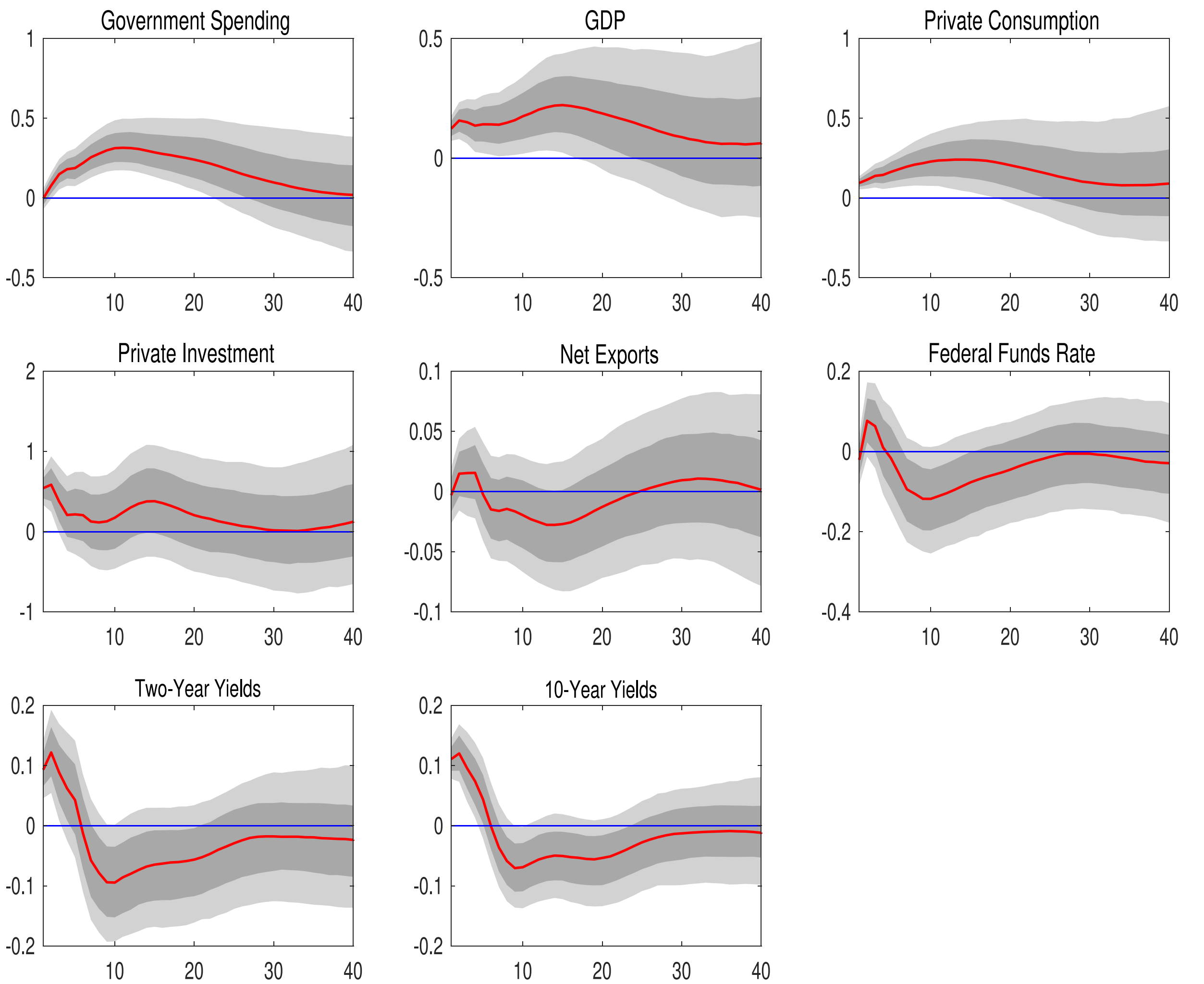

Fig. B.2. Empirical impulse response obtained by projecting the benchmark MFEV series onto news shocks based on Forni and Gambetti (2016) and replacing the government spending variable with the resulting residual. *Note*: See Fig. 1.

1. Federal funds rates: Effective federal funds rate, Item: FEDFUNDS, Source: FRED.
2. Treasury yields: Zero-coupon Treasury yields with maturities from one year to ten years, Source: Gürkaynak et al. (2007).
3. Population: Civilian noninstitutional population, Item: CNP16OV, Source: FRED.

Appendix B. Additional robustness checks

B.1. Excluding the NEWS *variable from the benchmark VAR*

The benchmark MFEV news shocks use information not only from the *NEWS* variable but also from exploiting the forecast error variance decomposition of government spending. To check the information provided by the *NEWS* variable, we delete the *NEWS* series from our data and re-estimate our benchmark VAR.

Fig. B.1 presents the results of this exercise.[13] Similar to the baseline results in Fig. 1, a news shock stimulates output significantly as well as crowds in private consumption and investment, leading both short-term and long-term yields to increase. The correlation of the MFEV news shocks without using the *NEWS* series and the benchmark shocks is 0.92, which, together with the IRFs shown in Fig. B.1, indicates that the *NEWS* variable adds little information to our large VAR system.

[13] In this appendix, we do not present the results related to the decomposition of interest rates when they are similar to the benchmark results; those results are available upon request.

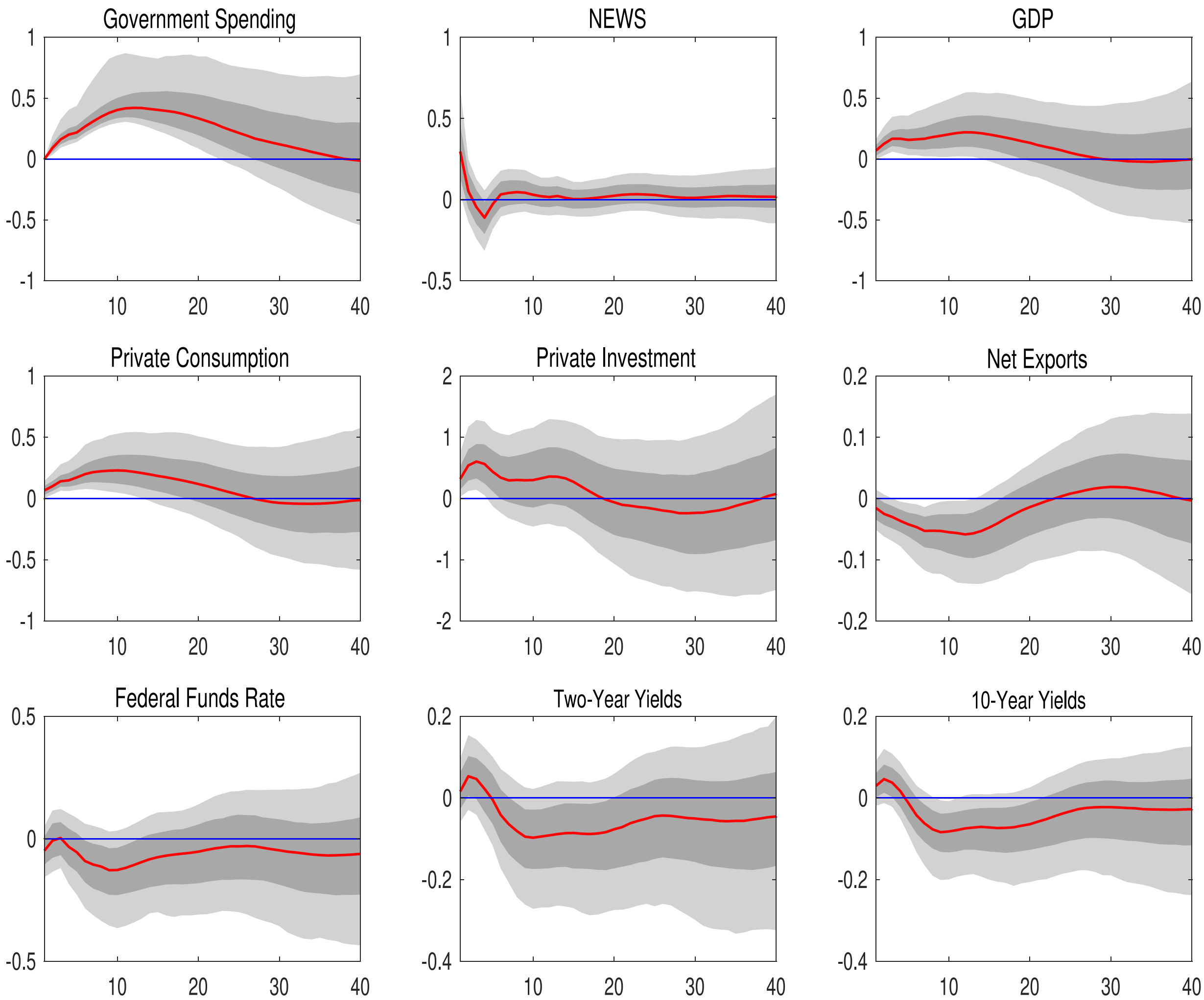

Fig. B.3. Empirical impulse response of the identified government spending news shock with a data set of 46 variables.
Note: See Fig. 1.

In addition, we follow Ben Zeev and Pappa (2017) to directly explore the information captured by our benchmark MFEV news shock series that is not captured by the news shocks based on Forni and Gambetti (2016), whose study mainly relies on the *NEWS* series. We project the benchmark MFEV series onto the news shocks based on Forni and Gambetti (2016) and place the projection residual first in the baseline VAR system[14] to estimate the impulse responses using recursive identification.

Fig. B.2 presents the results of this exercise. Compared with Fig. 1, all the results are qualitatively similar. In particular, the increase in both the short-term and the long-term yields is more significant. This exercise further suggests that the *NEWS* variable plays a limited role in generating our benchmark results.

In summary, the effects of government spending news shocks can be well estimated even without any information on the expectation of fiscal expenditures. Many studies such as Forni and Gambetti (2016) and Caggiano et al. (2015) use the forecasts of government spending to address the problem of informational insufficiency brought about by fiscal foresight. However, forecast data are not available for most countries. Our exercise demonstrates that a large VAR system can provide similar information to the variable constructed from the survey data. Therefore, extending our study to any country with sufficient macroeconomic and financial data would be straightforward.

The difference between the benchmark MFEV news shocks and news shocks based on Forni and Gambetti (2016) mainly comes from the different assumption made for the identification. The approach of Forni and Gambetti (2016) assumes that

[14] We also exclude the *NEWS* series as in Ben Zeev and Pappa (2017).

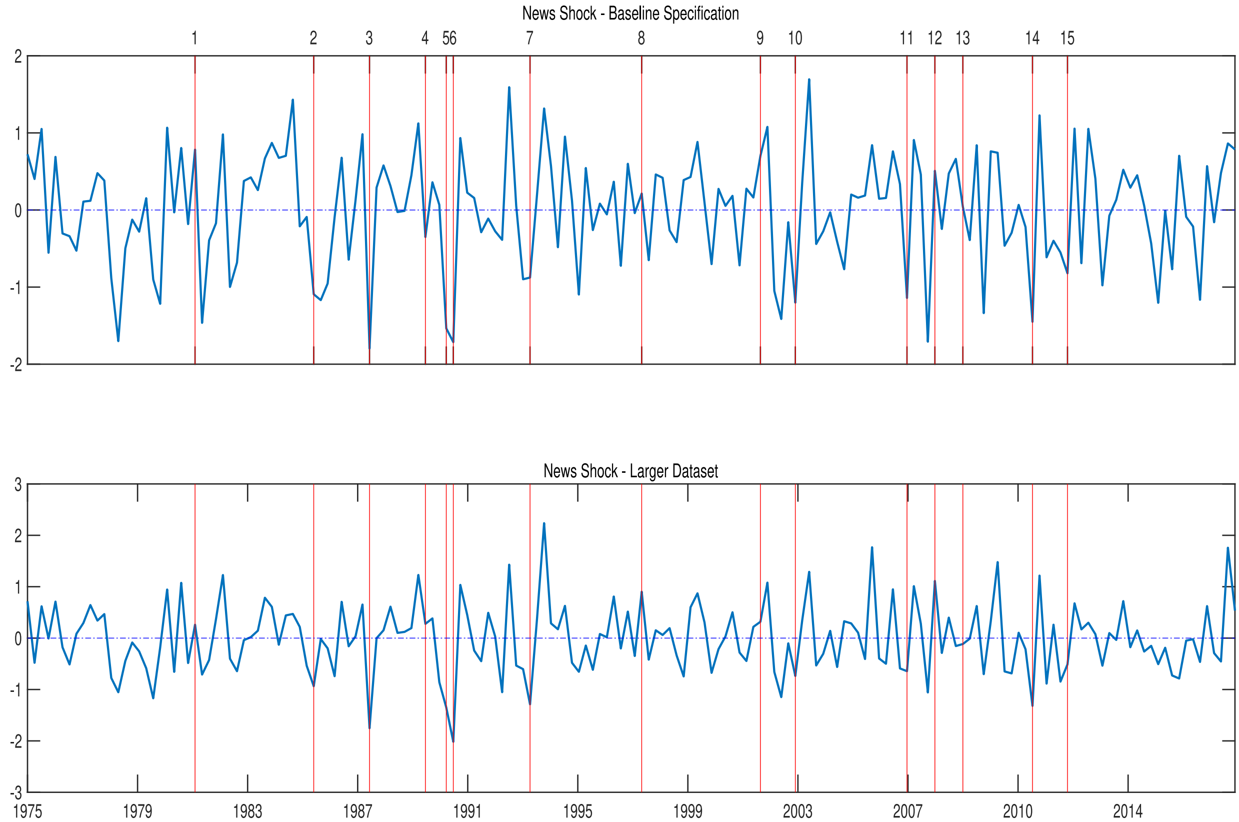

Fig. B.4. Top panel: News shock under the baseline specification; Bottom panel: Spending news shock under a larger data set. *Note*: See Fig. 8.

the constructed *NEWS* variable, which is the sum of the revisions of the expectations of government spending in our study, is unrelated to the present of all variables except government spending. By contrast, the MFEV approach identifies the news shock as the shock that best explains future movements in government spending over a finite horizon and that is orthogonal to current government spending. Since we include many financial variables and survey data in our large VAR system, the assumption that expectations of fiscal expenditure are not affected by the information provided by the present of these forward-looking variables seems strict.

B.2. Adding more variables into the benchmark VAR

We construct a larger data set (46 variables in total), which is similar to the large one with forecast data (43 variables in total) in Ellahie and Ricco (2017), to explore whether additional variables can improve our estimation of the impulse responses. Based on the large data set in Ellahie and Ricco (2017), we add the eight variables in our benchmark analysis: primary surplus, tax revenue, personal consumption expenditure, Baa/AAA spread, AAA/10-year Treasury spread, liquidity premium, net exports as a ratio of GDP, and two-year Treasury yields. We drop the forecast errors of government spending and the other four redundant variables such as imports, exports, AAA yields and personal service consumption expenditure.

Fig. B.3 displays the results of this exercise. Compared with Fig. 1, none of the results has changed qualitatively, although the posterior coverage intervals have become larger. The positive responses of two-year and 10-year yields are still significant at least at 68% posterior coverage intervals.

The correlation between the benchmark MFEV news shocks using 27 variables and news shocks using 46 variables is 0.8, which indicates that these two series share much in common. Fig. B.4 plots the two series with the same vertical lines as in Fig. 8. It is hard to claim that the estimated shocks using more variables are better than those using fewer variables. For example, our benchmark news shocks have a negative spike with the fall of the Berlin Wall, while the news shocks using 46 variables assign a positive value to this event.

In conclusion, additional variables change our benchmark results little. Further, a larger VAR system does not necessarily mean a better one. Giannone et al. (2015) show that the posterior mode (and variance) of the hyper-parameter, which

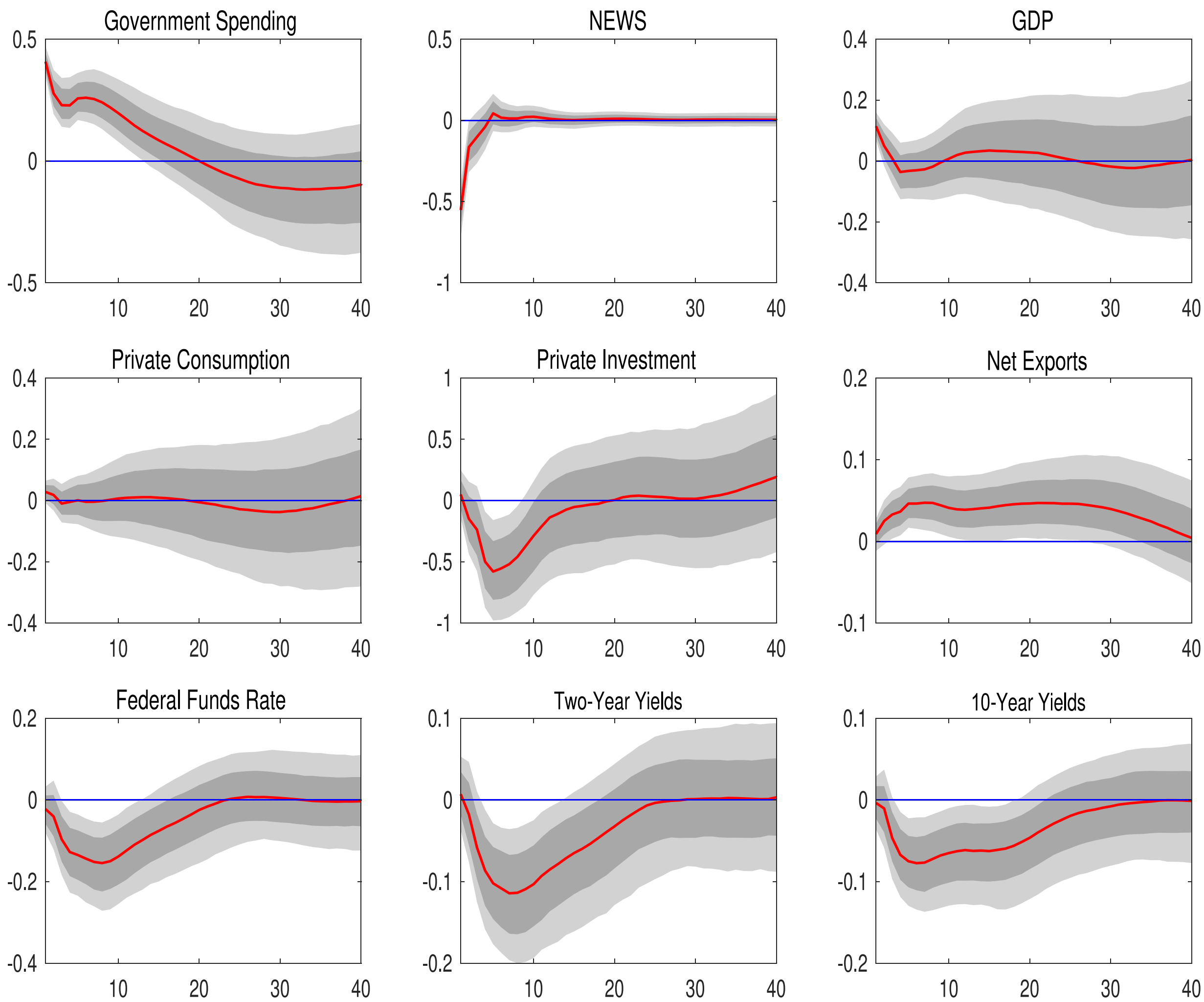

Fig. B.5. Empirical impulse response of the identified government spending surprise shocks using the proxy SVAR approach. *Note*: See Fig. 1.

determines the overall tightness of the Minnesota prior, decreases with the size of the model. The larger the size of the BVAR, the more likely it is that the prior information, not the data, dominates in the estimation, which is undesirable.

B.3. Identifying government spending surprise shocks using the proxy SVAR approach

For our MFEV identification strategy to be valid, the government spending surprise shock should be well identified. This exercise attempts to identify the government spending surprise shock using external instruments to further check the robustness of our benchmark results. Following Miyamoto et al. (2018), we use unexpected innovations in defense spending as our instrumental variable. This is calculated by $\Delta \log Def_t - F_{t-1} \Delta \log Def_t$, where $\Delta \log Def_t$ is the log difference in defense spending and $F_{t-1} \Delta \log Def_t$ is the one-period-ahead forecast of $\Delta \log Def_t$. Forecasts of defense spending are taken from the Greenbook data set, which is only available to 2012. Forecasts of federal spending from the Survey of Professional Forecasters are used to calculate unexpected innovations in defense spending after 2012.

In the application of the proxy SVAR approach, good candidates for instrumental variables must satisfy two conditions. First, the instrument should be correlated with the shock of interest (relevance). We regress the VAR residuals with respect to government spending on unexpected innovations in defense spending and the resulting first-stage F-statistic (62.76) is well above the recommended value of 10 usually required for relevant instruments in the proxy SVAR approach. Second, the instrument should be uncorrelated with the remaining shocks (exogeneity). U.S. national defense spending is dominated by foreign political events, which is usually unrelated to the state of the U.S. economy. Ben Zeev and Pappa (2017) plot the responses of defense spending to different shocks that are considered to be important sources of business cycle fluctuations. The results are always insignificant, which indicates that defense spending appears to be exogenous.

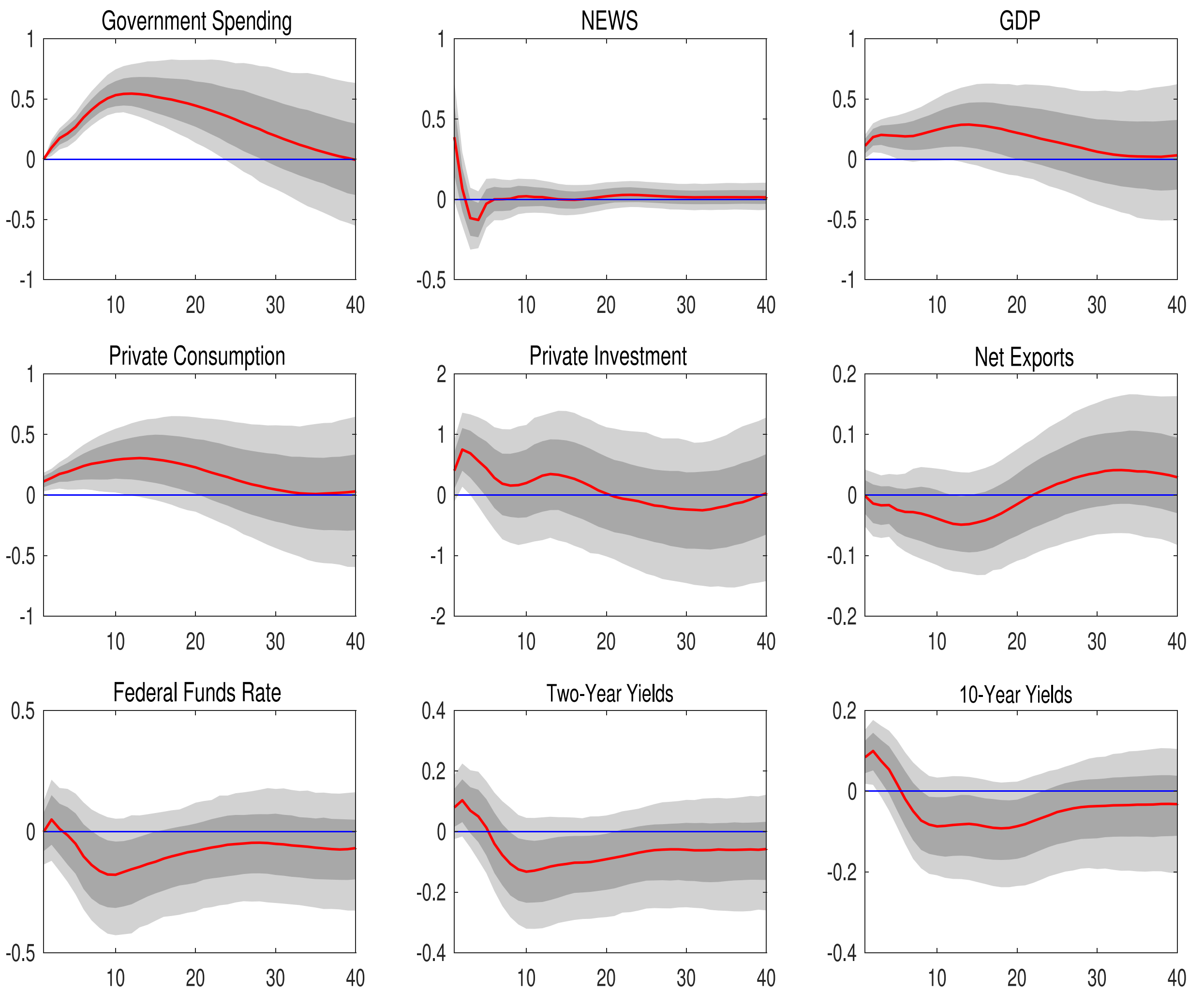

Fig. B.6. Empirical impulse response of the identified government spending news shocks using the MFEV approach, while the surprise shock is identified using the proxy SVAR approach. *Note*: See Fig. 1.

Figs. B.5 and B.6 present the results based on the proxy SVAR approach for a surprise shock and a news shock, respectively. With regard to the news shock, all the variables in Fig. B.6 and Fig. 1 behave qualitatively identically, which suggests that the effects of government spending news shocks are robust when government spending surprise shocks are identified using different identification schemes.[15]

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[15] The inference in this exercise suffers from the criticism of Arias et al. (2018), which needs to be improved in future work.

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